Comparison of Clustering Methods over a Hidden Web Data using Stratification

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ABSTRACT

This paper's centre of attention is on the problem of data mining (in general) and clustering (in specific) on a hidden web data. We know that data mining is a process that analyzes and extracts knowledge from large amounts of data which provides useful information to users. Hidden or deep web data is the database located at remote system .So, to access such data, we need query interface or HTML forms. Clustering such type of data is difficult as it is limited to indirect access through query interface and requires more time to access. A novel methodology stratified clustering introduced through sampling of datasets. The samples can only be obtained by submitting queries. It is required to apply efficient sampling method to reduce time consumption and number of queries required to access deep web data. This paper proposes series of steps to accomplish the task.1) the space of input attributes are categorized into stratum that represents the association between input and output attributes.2) Efficient sampling method proposed to obtain high estimation accuracy .3) the samples obtained are used by two clustering methods, stratified k-means clustering and hierarchical clustering. The estimation accuracy of cluster centers of deep web data are compared for simple random sampling against stratified sampling and k-means clustering method against hierarchical clustering method.

Keywords

Stratification, Stratified Sampling, Stratified k-means

Clustering, Stratified Hierarchical clustering;

1. INTRODUCTION

In current days, one of the approaches of data distribution became most popular is hidden web. Hidden web data contains large amount of data stored in the form of database located at remote system. It can be accessed through internet by submitting user queries using HTML forms called query interfaces. Hidden or deep web is qualitatively different from surface web [4]. Many recent efforts took place for the development of deep web querying systems to provide an interface between deep web and users [3, 5 and 6]. It is advantageous to obtain the summary for an existing deep web data source. For example, consider car dataset (as inTable1). The summaries of car details for a specific range of price attribute values highly useful for purchaser or customer. The main approach of this paper is to cluster the deep web data that presents interesting information to users and compares two clustering methods.

2. LITERATURE SUMMARY

The various existing sampling methods for clustering, sampling for different data mining problems and sampling for hidden web discussed.

Clustering based on Sampling

The various sampling methods are widely studied by many researchers. CLARA is one of the best methods for clustering huge amount of data based on sampling that finds best potential medoids [2].

Distinct Data Mining Problems based on Sampling

One of the data mining methods is frequent item set mining. This is studied by several researchers. Toivonen developed random sampling method to find association rules, proved by considering entire dataset [1].

Sampling Methods for Hidden Web Data

There have been several research efforts for sampling from deep web data. Dasgupta et al proposed HDSampler, to retrieve random sample through query interface from deep web data.

3. METHODOLOGY

In this section, the concept of components to achieve the goal of obtaining cluster centers of output attributes of deep web data source is discussed.

3.1 Stratification

Stratification is the process of partitioning the entire deep web data source into homogenous groups with minimized variance within each group. These homogenous groups are also called as strata or stratum. Stratification helps to improve performance for sampling and reduce error in the estimation of cluster centers in deep web data source. Also, finds the relationship between input and output attributes. Stratified sampling is a process of choosing sample from each stratum. Stratification helps to obtain a sample that represents actual distribution of deep web data.

The input attribute that decreases the difference of output attribute values is considered to stratify the data. This process is done in the form of tree structure [8]. It is done in a greedy process, in which each node of a tree represents query with input attribute subspace and leaf nodes represents stratum. At each node, there will be a set of potential splitting input attributes; among them one input attribute is chosen to further stratify the data so that the variance within each stratum is small.

This process continues until there is no further input attributes to stratify or if specified threshold value is greater than the radius of data records within the stratum.

For example, consider the car data set shown in table 1 with 20 records. It is clearly observed that the value of output attribute price varies accordingly depending on the input attribute model. So we can consider "model" attribute to stratify the data.

In deep web data source, consider set of input attributes IN = {IN_1, IN_2, INn}, set of output attributes OP = {OP_1, OP_2,… OP_n}. Now, say for a query input subspace for each leaf node of tree contains subset of input attributes S, (S∈ *I*N) input attributes not contained in current query subspace is said to be potential set of splitting input attributes i.e., P={IN –S}. The Radius of query sub-space is,

Radius = $\sqrt{\frac{\sum_i (D(OP)-CS)^2}{N}}$ R=1920; for strata sub-population1

Here, D (OP) denotes the vector of output attributes, CS denotes the centre of sub-population i.e. mean value, and N represents the size of population.

For an input attribute PI_i, the decrease of radius,

ΔR_i =Radius-$\sum_{k=1}^{t} p($ Pi =$d_{i,k}$ |Q) × $R_{i,k}$;

ΔR_i=199; for sub-space with Input attribute:'Service'

ΔR_i=1413; for sub-space with Input attribute:'mileage'

Here, p (Pi =$d_{i,k}$|Q) = P (Pi =$d_{i,k}$, Q)/p (Q) represents the conditional probability of input attribute P_i, $d_{i,k}$ represents the k=1…, t domain values. Assume, deep web data provides the prior probability of P (Pi =$d_{i,k}$, Q) and p (Q), hence p (Pi =$d_{i,k}$|Q) can be obtained. $R_{i,k}$ is computed similar to the radius formula for kth potential child generated by splitting with input attribute P_i.

For example, consider car dataset. First we consider "Model" attribute to stratify the data as it clearly decreases radius of "price" attribute within strata. Now, calculating decrease of radius for "service" (ΔRI=199) and "mileage" (ΔRi=1413) attributes, "mileage" has the highest decrease of radius. Hence, input attributes "mileage is considered to further stratify the data.

Figure 1 show the tree structure representation of stratification of data which was presented in the table1, with leaf nodes representing stratum. Initially, data records stratified considering the input attribute "model" (with values 'Toyota Corolla' and 'To Sienna LE').Again these sub-populations are sub-divided into strata considering input attribute "mileage" with domain range of values= {(5000 to 20000),(20000 to 45000),(45000 to 90000)},as decrease of radius is highest for "mileage" attribute compared to "service" attribute. This greedy stratifying process stops when the radius associated with all leaf nodes is smaller than a pre-specified threshold.

The obtained strata later used for stratified sampling.

3.2 Effective Sampling Method

The Stratification process results in set of strata. The traditional Simple random sampling can be performed to choose random number of data records from each stratum. Random sample data may not represent the accurate deep web data source. The efficient sampling method Neymann allocation method [10] can be applied to obtain number of data records to be drawn from each stratum. The proposed sampling method reduces the error in the estimation of distribution of deep web data and also reduces access cost. The cost here represents the number of queries required to access data.

The obtained sample represents the actual distribution of deep web data source and further used for stratified clustering.

3.3 Stratified Clustering Methods

In this section, clustering methods over a stratified sample obtained from deep web data source is introduced. As sample obtained is not a simple random sample, traditional k-means or hierarchical clustering cannot be applicable. So, we go for a novel clustering methods *stratified k-means clustering* and *stratified hierarchical clustering.*

3.3.1 Stratified k-means Clustering

In stratified sample, each data record is associated with a certain weight. Stratified k-means clustering is similar to original k-means clustering, but it considers weight of a data record of sample [8]. Let us consider a sample SS, assume n_j records are drawn from jth stratum, corresponding stratum contains N_j number of data records. Then, we can say each data record in the sample is associated with the weight of $\frac{N_j}{n_j}$.

The novel clustering method works same as traditional k-means clustering. The difference is at each iteration the centre of cluster is associated with weight of data record. Similar to k-means clustering, centre of ith cluster is

$$C_i = \frac{\sum_m wt_m \times D_m\ (OP)}{\sum_m wt_m};$$

Two cluster centres, C_1=4142.82; C_2=23985.5;

Here, D_m(OP) represents the vector of output attributes for data records belonging to cluster, wt_m represents the weight of data record $\mathbf{D_m}$ and m denotes number of data records in a cluster.

The performance of clustering depends on number of clusters k. To achieve good results, the algorithm can be repeated many number of times, the smallest distance within the clusters will be taken as final result. The distance within the clusters is obtained by,

CRDist=$\sum_{i=1}^{k} \sum_{i=1}^{|C_i|} wt_m\ distance\,(D_m(OP), c_i)$

where *Ci* represents the set of data objects belonging to the *i*th cluster in the sample, distance(D_r(OP), c_i) denotes distance between data records and center of cluster.

For example, consider two strata are generated from the values shown in table 1, with input attribute values "Toyota Corolla" and "Toyota Sienna LE". consider a sample drawn from these two stratums with n1=5 and n2=5 number of data records from each stratum and consider output attribute price values of, Sample from 1st stratum = {15995, 12495,16277,13995,12956} Sample from 2nd stratum = {22995, 12888, 24977, 25975,21995}. Using stratified k-means algorithm, cluster centres obtained are C_1=14142.82 C_2= 23985.5

Hence, the output of stratified k-means clustering is estimated two cluster centres of deep web car data are obtained.

3.3.2 Stratified Hierarchical Clustering

In this approach, Similar to stratified k-means clustering process discussed above, the original hierarchical clustering works with the difference is it considers weight of each sample record. Let us consider a sample NS, assume n_j data records are

drawn randomly from jth stratum, the corresponding strata contains N_j data records. Hence, each data record in the sample

represents $\frac{Nj}{nj}$ data records in jth stratum. Correspondingly, in our clustering process, each data record in the sample is associated with weight of $\frac{Nj}{nj}$. An algorithm [9] works in the following way.

Similar to the traditional hierarchical clustering methods, at each step, two clusters with the minimum distance are merged into one cluster. The process continues until there are k clusters left, where k is the predefined number of clusters.

The distance between two data records is computed as the Euclidean distance on the output attributes. Formally, for two data records D1∈ NS, D2∈ NS from the deep web data source with the set of output attributes OP, the distance is computed as:

Distance(D1,D2) = $\sqrt{\sum_j (O_{1,j} - O_{2,j})^2}$ where, the output attribute Oj ∈ OP. The distance between two clusters, C1, C2, is the average of the weighted distances between all pairs of two data records Di ∈ C1, and Dj ∈ C2,

i.e., Distance(C_1,C_2)= $\frac{\sum_i \sum_j wt_i \times wt_j \times Distance(D_i, D_j)}{\sum_i \sum_j wt_i \times wt_j}$;

Dist(C_1,C_2)=67; Dist(C_1,C_3)=106; Dist(C_2,C_3)=76;

where ωt_i, ωt_j denote the weights associated with data records *Di* ∈ *C*1 and *Dj* ∈ *C*2 respectively.

For example, consider two strata are generated from the values shown in table 1 with input attribute values "Toyota Corolla" and "Toyota Sienna LE". Now, say a stratified sample is drawn from two stratum with n1=5, n2= 5 number of data records from each stratum. The ouput attribute price values of,

Sample form 1st stratum= {15995,12495,16277,13995,12956}

Sample from 2nd stratum={22995,12888,24977,25975,21995}. Here, as there are 10 records , as in hierarchical clustering 10 clusters are generated. For a given number of clusters k=3, using above distance formula , we obtain distance between these clusters as:

Dist(C_1,C_2)=67; Dist(C_1,C_3)=106; Dist(C_2,C_3)=76;

Clearly, distance between clusters C_1 and C_2 is lowest , so it can be merged to form a cluster, thus we attain two clusters using hierarchical agglomerative clsutering with stratified sample.

Representation of Clusters

The clusters are represented by their centre vectors. In traditional clustering methods, the centre vectors are computed as the mean vectors of the data records assigned to the same cluster. This cannot be used directly in the stratified clustering, where the data is not randomly drawn from the entire population. Thus, the centre vectors are computed as the weighted average of the data records assigned to the same cluster. For the ith cluster C_i, the centre vector is computed as:

$$\overline{cc_i} = \frac{\sum_m wt_m \times o_m}{\sum_m wt_m};$$

$\overline{cc_1}$=15228.71 ; $\overline{cc_2}$=24649; for two clusters obtained above.

here o_m corresponds to the vector of output attributes for the data record D_m ∈ C_i. The associated radius R_i for cluster C_i is estimated as:

$$\overline{Radius_i} = \frac{\sum_m wt_m \times Distance(o_m, \overline{cc}_i)}{\sum_m wt_m}$$

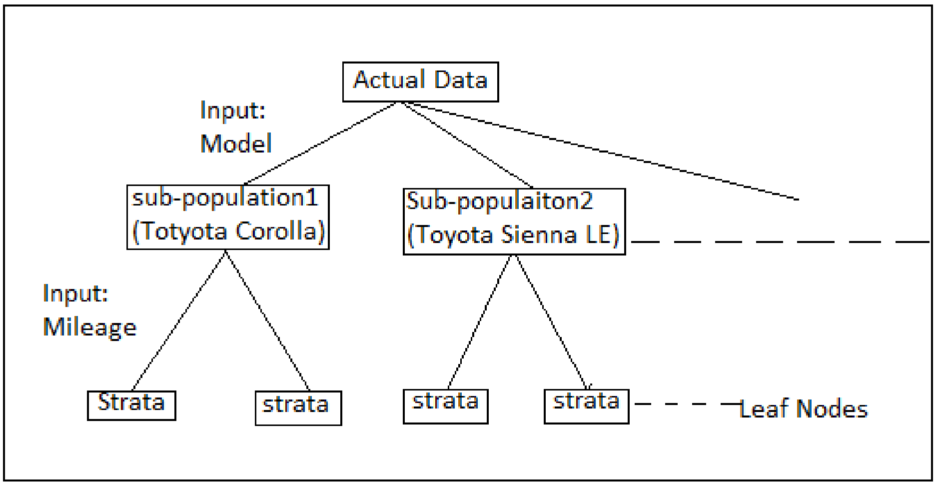
where $Distance(o_m, \overline{cc}_i)$ denotes the Euclidean distance on output attributes. The Radius associated with in the cluster is used to find the best number of clusters, the clusters with smallest radius within the cluster is considered as the final cluster centers as output.

Table 1. An Example of Deep Web Car Data set

S.NO	MODEL	NO. OF DOORS	SERVICE	MILEAGE	PRICE
1	Toyota Corolla	4	3	11655	15995
2	Toyota Corolla	4	3	13324	15995
3	Toyota Sienna LE	4	2	39497	22995

4	Toyota Sienna LE	4	2	41670	22991
5	Toyota Sienna LE	4	2	45370	21995
6	Toyota Corolla	4	3	32107	12495
7	Toyota Corolla	4	3	5928	16277
8	Toyota Corolla	4	4	67515	10999
9	Toyota Corolla	4	2	40697	13995
10	Toyota Sienna LE	4	9	80279	12888
11	Toyota Corolla	4	3	61000	12499
12	Toyota Sienna LE	4	3	38694	19995
13	Toyota Sienna LE	4	1	18610	24977
14	Toyota Sienna LE	4	1	14648	25888
15	Toyota Corolla	4	3	34697	13799
16	Toyota Corolla	4	4	44468	12956
17	Toyota Corolla	4	2	11792	15900
18	Toyota Sienna LE	4	11	103651	8995
19	Toyota Corolla	4	4	88419	10900
20	Toyota Sienna LE	4	1	13922	25975

Figure 1. The Process of Stratification in the form of Tree Structure



4. EXPERIMENTAL ANALYSIS

In this section, the comparison of two clustering methods hierarchical and k-means clustering, simple random sampling against stratified sampling proposed using weka tool [7].

Synthetic data set: This data set is generated using simple java application that creates any number of specified rows with four categorical input attributes and one numerical output attribute.

Yahoo Data set: The Yahoo! Data set consist sampled web data from real world hidden web data at http://autos.yahoo.com/. It consists of four categorical input attributes *model, service, number of doors of, mileage* and one numerical output attribute *price.*

The tables shown below represent the comparison of two clustering methods k-means clustering against hierarchical clsutering, and *simple random sampling (SRS)* against stratified

Sampling. Here, stratified sampling is obtained using supervised filter in the weka tool that subsamples the data set by stratification.

As the mean squared error values is larger for simple random sampling methods than supervised (stratified) sampling, the clusters efficiency is more based on stratified sampling method. It is clearly shown in table that, time required to build a model for k-means clustering is smaller than hierarchical clustering, hence the scalability of k-means clustering is more than hierarchical clustering.

The Proposed method stratification process stratified clustering and sampling method discussed in section3 improves the efficiency of sampling and clustering, in specific larger databases located at remote system.

Table 2. Comparison of Clustering Methods and Sampling using Synthetic Data set

Sample size	k-means clustering				Hierarchical Clustering	
	Simple Random Sample(SRS)		Supervised Sample(SS)		SRS	SS
	Sum of squared errors within cluster	Time to build model	Sum of squared errors	Time to build model	Time to build model	Time to build model
400	482.07	0.02s	407.10	0.02s	0.24s	0.17s
800	959.48	0.06s	840.64	0.04s	1.35s	0.28s
3000	3605.59	0.11s	3183.11	0.08s	38.05s	16.4s
5000	5956.20	0.2s	6603.43	0.18s	72s	52s

Table 3. Comparison of Clustering Methods and Sampling using Yahoo Data set

Sample size	k-means clustering				Hierarchical Clustering	
	Simple Random Sample(SRS)		Supervised Sample(SS)		SRS	SS
	Sum of squared errors within cluster	Time to build model	Sum of squared errors	Time to build model	Time to build model	Time to build model
100	185.79	0.01s	172.92	0s	0.03s	0.01s
300	547.81	0.01s	528.29	0.01s	0.08s	0.07s
500	950.95	0.01s	920.03	0.01s	0.31s	0.19s
800	1250.93	0.02s	1100.02	0.01s	0.36s	0.28s
1000	1847.19	0.03s	1847.19	0.01s	1.28s	1.15s

5. CONCLUSION

In present days, growing in the usage of internet by vast number of users, data in the deep web is increasing. Clustering on such type of deep web data, obtaining summarized results presents user with interested information. This paper proposed a new methodology for clustering on deep web data using stratified k-means clustering and hierarchical clustering. The proposed stratified sampling and neymann allocation method improves the performance of clustering. Comparison of clustering methods, deep web sampling methods analyzed using weka tool. The experimental analysis resulted that k-means clustering is more

scalable than hierarchical clustering, stratified sampling results in high performance compared to simple random sampling.

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