INTERNATIONAL JOURNAL OF ADVANCE RESEARCH, IDEAS AND INNOVATIONS IN TECHNOLOGY

ISSN: 2454-132X
Impact Factor: 6.078
(Volume 7, Issue 4 - V7I4-1473)
Available online at: https://www.ijariit.com

Clustering of JSON document using Derived X-Path Method

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Abstract—In this modern era where data creation is in abundance, handling that data is the biggest question researchers havebeen trying to solve for the past couple of decades. The data in any form needs to be stored in such a way that the retrieval and manipulation of the data are easier and simpler. In this paper, welook at how huge datasets in JSON format are being analyzed andmade into clusters for an easier understanding of the documents that we are handling. This process is done by the first pattern analyzing the documents followed by clustering those documents one by one based on similarity of the attributes (arrays and sub-documents included). The clusters are then evaluated on an algorithm designed specifically for this purpose. To conclude, thispaper lays out the model on how to cluster huge JSON documents with varying levels and types.

Keywords— *JSON, Cluster, Schema, Attributes, Similarity, Decision Tree, X-Path*

1. INTRODUCTION

The proposed work aims to discuss and focus on how JSON documents are clustered. To begin with, what are JSON and its uses. JavaScript Object Notation (JSON) is a data format/ data structure that is used extensively to store information ina tree-like structure for more organization and easy access way. This format of data is usually used between server and a client browser embedded with Java scripts and HTML files to ease the communication between the same. It provides many details into the type of data by being able to hold meta- data along with the original data. This type of data makesit easier since there is no need for interpretation into another language since the metadata provides the information requiredon both ends. JSON is a lightweight data-interchange format, ”self-describing” and easy to understand. It is language- independent, and why we used this is because the JSON formatis text only; it can be communicated between servers and the much simpler data format allows for easier parsing. JSON enables faster accessibility, memory optimization is shorter and simpler in nature, and does not contain complicated syntaxtags.

Let’s move on to the limitations of JSON. It is not fully secure. It is limited in terms of the supported data types. There is another issue with JSON as it is quite weak with respect to security. If this JSON is used as the medium of communication with an untrusted service, then there is a possibility of malicious attack during the transmission sincea JSON service that is returned is wrapped in a function call.

This function call can be used by untrusted certificates that can call this object and can lead to loss of data to the intended receiver.

Clustering is a unique technique for machine learning on unsupervised data. Clustering is the process of segregating the whole group of data points into a number of groups ina strategic way. By strategic, we mean that the clustering of these data points must have some logic as to the clustered datapoints have maximum similarity among them. This means thata given point must have more similarities to the correspondingdata point in the same cluster than any other point in the wholeset. This paper explores an entirely python-based approachto JSON Clustering and its feasibility on multiple factors like developer friendliness, deployment interface, efficiency, and scalability. Since this paper also considers the complete structure of the document, the inter-cluster and the intra-cluster similarity is high. The clusters are formed during a single scanof the dataset, which helps in avoiding the multiple scans of the dataset, which in turn reduces the time hence speeding up the Clustering Process.

The further section gives a brief overview of the literature survey done as part of the project. Section 3 shows the motivation behind this project—section 4 details the methodology, including the algorithms used. Section 5 summarizes the paper,also touching upon the limitations of the project and potential future work. Section 6 gives the results. Section 7 gives the final conclusion of our project and section 8 gives a list of references.

2. RELATED WORK

Some studies on JSON in the clustering environment have been carried out as yet. This paper aims to deal with the clustering application and the implantation aspects of clustering with

JSON . In fact, a wide variety of Clustering's has been developed during the last few years. These reviews are more or less described separately in the corresponding literature. This section refers to some review papers which pertain to the JSON Clustering Framework and outlines their main advantageous and disadvantageous features.

So, referring to the query optimization and analysis of document-oriented databases[1], we found that the document-oriented databases end up in a very tedious state where there is a large amount of data, and this data cannot be analyzed in the fastest time possible. Since JSON follows an unordered-list type of format, we have no idea of how the attributes relate to one another and where one attribute might definitely occur. for this very reason, there aren't many research options to cluster these databases. Hence, we tried to look at the optimized way of representing the JSON documents but were unable to find anything related to optimizing it for further analysis.

There is a process called schema profiling[2]. In schema profiling, they try to figure out the hidden rules in document-oriented databases like JSON, which is further used to ex- plain the variance that is occurring in these datasets. Schema profiling represents these data in the form of a decision tree, which in the end tries to cluster the data. We use schema profiling to build a similarity tree as the schema profilingas per the author. This process provided much better results than going step by step analysis of the JSON documents asit instantaneously profiled all the similar documents, and we were able to calculate the score of the documents. Though thisprocess seemed to be optimistic, we still couldn't figure outthe exact similarity score for the given JSON document and hence were still researching on finding one. In a schema-basedsplit the vertice (say v) has two children and the correspondingedges are labelled, while in a value-based split v has two or more children and the corresponding edges are labelled with a condition expressed over the domain of a. Note that, while anysplitting value "val" can be adopted for value-based splits on numeric attributes and binary splits on categorical attributes truing to deal[3] with a structure and content semantics underlying semi-structured documents, which is challenging for any task of document management and knowledge discovery conceived for such data. In this work, it is addressed thatthe novel problem of clustering semantically related XMLdocuments according to their structure and content features. Due to this semi-structure of XML, it has raised a lot of issues on representation and extraction of data. A lot of resources have been contributed in order to solve this semi-structure of XML documents and has led to a decrease in the semantic issue up to a certain extent[4].

In [5], they had presented a comprehensive review of structural XML clustering. First, it is provided with a basic introduction to the problem and highlight the main challenges in this research area. Subsequently, later divide the problem into three subtasks and discuss the most common document representations, structural similarity measures, and clustering algorithms. In addition, they also presented the most popular evaluation measures, which can be used to estimate clustering quality. Finally, moving to the clustering part, where mostof the XML clustering approaches developed so far employ pairwise similarity measures.

It is essential to point out that the reviewed papers did not present the use cases and benefits of Clustering applications in alternative areas, especially with respect to JSON documents. This paper has classified the exploring and sharingof the Clustering framework. On the other hand, the existing implementations of the Clustering framework and their pros and cons are not included in the published papers thoroughly.

3. MOTIVATION

As we can see, the computerized field has a lot of options for storing and sharing data. So, we can see XML being a data-interchange format. But along with XML, even JSON isa data-interchange format. Although JSON has seen its part in improvements in the field of data analytics, there has always been a bias when it comes to the classification of data. XML has always been easier to classify, given its much familiar format and API services available to it. Given XML has a largeamount of data, this data can be classified within few minutes because of the highly optimized algorithms already in place. When it comes to JSON, there has not been an algorithmthat has been developed yet to overcome that bias towards XML. As one of the best data formats for accessing, storing and comprehending data. JSON is even better with parsingas XML docs are difficult to parse. JSON is even faster and easier than XML. According to researchers view, there area lot of researches going on in the field of XML, including XML clustering. Even though with all these advantages over XML, we cannot find an algorithm that can classify a JSON document in the most accurate and optimized way.

4. METHODOLOGY

Accessing all the attributes: To access the sub-level at-tributes, we maintain a queue of attributes for a document. Whenever a new attribute is encountered, its children are addedto the queue. If an attribute has an array of objects as itsvalue, then we include the attributes of the object in the queue.When the end of a level is reached, '-1' is added to the queue, indicating the same. Once we encounter two consecutive '-1', the end of the document is reached. This is how multi-level accessing is achieved.

Formation of the attribute tree: In the attributes tree, when- ever we encounter an attribute, we search for the node withthe same name in the children of the current node it resides.If there is a node with the same name, we move to that node, and this becomes the current node. A new node is formed as the children of the current node; if there is no similar node in the children of the current node, it exists.

Formation of the cluster tree: Whenever a new cluster is formed, we create a node of that cluster and add it to the clustertree. If the new cluster already shares common attributes with previously existing clusters, then the new cluster is added asa child of the existing cluster. If the new cluster does notshare any common attributes, then it is added as the childof the cluster tree root. This is an independent cluster. Fig 1 shows how the clusters are formed. Below is the process of calculating similarity score.

```
1)  while 0:2 threshold 0:9 do
2)  Reset attribute Tree
3)  Reset cluster Tree
4)  Reset Optimal Tree
5)  while q n do
6)  fcurrentNode traverses all of the attributes in the at-
tributeTreeg
7)  for k in currentNode:children do
8)  if node already exists in attribute tree then
9)  currentNode = currentNode:children
10) matchCount = matchCount + 1
11) else
12) if matchCount¡(threshold clusAvgLen) then
```

```
13)    create new node in attributeTree with new cluster number
14)    create a node in clusterTree
15)    else
16)    create new node in attributeTree with same cluster number
17)    add a node with the current document number to the node with current cluster number in cluster tree
18)    fclusAvgLen = (clusAvgLen + attributeCount) / 2g
19)    //fclusAvgLen is average length of the clusterg
20)    //fattributeCount is length of the current documentg
21)    PROCESS - update clusAvgLen
22)    PROCESS - calculate the similarityScore
23)    PROCESS - Update the Optimal Tree
24)    PROCESS - Print similarityScore of each threshold and optimal tree.
```

- Line 1 sets the threshold for similarity from 0.2 to 0.9. Line 2-4 sets the attribute tree and cluster tree for the current threshold.
- Line 5 makes the code scan through all of the documentsin the dataset.
- Line 7-20 scans through each of the attributes in the document
- Line 8-10 checks the condition to create a new node inthe attribute tree
- Line 11-18 We create a new node in the attribute tree and check the condition to form a new cluster.
- Line 12-14 Creating new cluster
- Line 15-18 Updating the current clusters
- Line 21 Update the cluster average length
- Line 22 Measuring the similarity score
- Line 23 Updating the Optimal Tree
- Line 24 Printing the final attribute tree.

To calculate the similarity score, we have used a measurement metric similar to the f1-score. Like the way we have precision and recall in f1-score, we have an inter-cluster and intra-cluster similarity. The precision and recall behave inversely. Ifprecision is high, recall is low and vice versa. Let's consider that there are 4 clusters formed: c(1),c(2),c(3),c(4) Intra-clustersimilarity of cluster c(1) is calculated by the formula: Y(i) = number of common attributes in c(i) total number of attributesin c(i) Inter-cluster similarity is calculated as follows: inter- cluster similarity of cluster c1 is calculated as:

$$X_i = \sum_{i=1,j=1}^{n} (C_i, C_j) + 1 \qquad (1)$$

But inter-cluster and intra-cluster similarities are directly proportional. When the threshold is less, the intra-cluster similarity(Y) is less because even though the attributes are different, they form the same cluster. The inter-cluster(X) similarity is also less since there are very few common attributes among them. When the threshold is high (0.9), the intra-cluster similarity(Y) is high since the no. of common attributes must be high to form the same cluster. The inter- cluster(X) similarity is also high since even though they have a lot of common attributes, they cannot form a cluster. (If two docs have eight similar attributes out of 10, they won't form a cluster (0.8 thresholds)). So, to reflect the inverse behaviour of precision and recall, we have taken the inverse of intra-cluster similarity value. The reason why we didn't take the inverseof X is that this can have values of 0. Hence 1/(X+1) will be one, and this doesn't become a good balancer of the value. ButY1 can never become 0; it is always greater than 0 and less than 1, so 1/Y never becomes 1. Hence this is a good balancer of the values. The formula to calculate the similarity score is similar to the f1-score. During experimentation, we found thatconsidering the inverse of X can lead to biased results, which shows high similarity scores for thresholds 0.2 and 0.9.

Similarity Score:

$$2 * \Pi_{i=1}^{n}((X_i + 1) * (1/Y_i)) / \sum_{i=1}^{n}((X_i + 1) * (1/Y_i)) \qquad (2)$$

5. LIMITATIONS

The limitation of our algorithm is that it doesn't work for duplicate keys on the same level since the keys that are taken from the level are given a unique key. Hence if there are any duplicate values, it creates a dictionary with duplicate values, and it leads to a key error in the dictionary. The other limitation that is similar to the above is the unique values in the array must exist since the same functions are used to solve the array problem. The format of JSON should be in the standard JSON format of the original dataset. No other data structures other than arrays, objects and fields are allowed in the dataset.

This work has not been done by any of the research communities that are working on the clustering of the documents. So, this is an addition to the research space. The algorithm was compared with the existing Weka algorithm for various standards. According to our evaluation measure using the F1-score, the Weka was also tested with multiple data sets and was compared with our algorithm. The results proved that our algorithm fared better than the d-tree model due to the high time complexity and decision making in the d-tree Model. Since the model is very sophisticated at the fundamental level, it creates a very complex tree which is really not what our algorithm does and hence a better result output. The following images compare the results of the d-tree and our algorithm on the same data set.

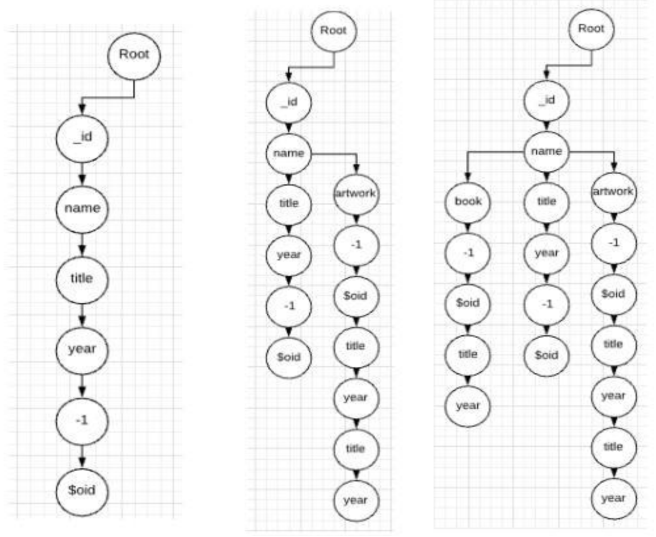
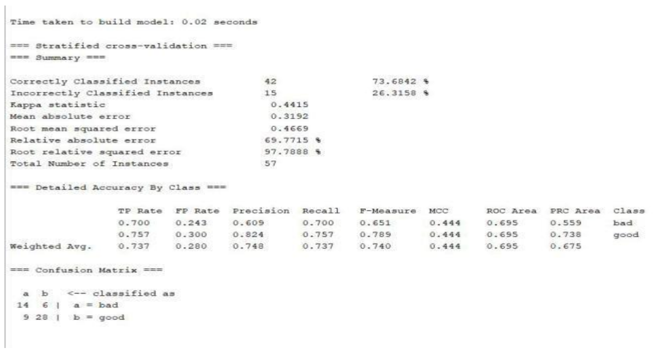
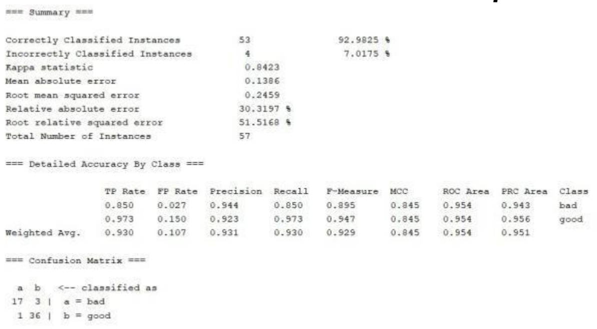


Fig. 1. Cluster Formation



```
Time taken to build model: 0.02 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          42               73.6842 %
Incorrectly Classified Instances        15               26.3158 %
Kappa statistic                          0.4415
Mean absolute error                      0.3192
Root mean squared error                  0.4669
Relative absolute error                 69.7715 %
Root relative squared error             97.7888 %
Total Number of Instances               57

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.700    0.243    0.609      0.700    0.651      0.444    0.695     0.559     bad
                 0.757    0.300    0.824      0.757    0.789      0.444    0.695     0.738     good
Weighted Avg.    0.737    0.280    0.748      0.737    0.740      0.444    0.695     0.675

=== Confusion Matrix ===

  a  b   <-- classified as
 14  6 |  a = bad
  9 28 |  b = good
```

Fig. 2. Efficiency Result



```
=== Summary ===

Correctly Classified Instances          53               92.9825 %
Incorrectly Classified Instances         4                7.0175 %
Kappa statistic                          0.8423
Mean absolute error                      0.1386
Root mean squared error                  0.2459
Relative absolute error                 30.3197 %
Root relative squared error             51.5168 %
Total Number of Instances               57

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.850    0.027    0.944      0.850    0.895      0.845    0.954     0.943     bad
                 0.973    0.150    0.923      0.973    0.947      0.845    0.954     0.956     good
Weighted Avg.    0.930    0.107    0.931      0.930    0.929      0.845    0.954     0.951

=== Confusion Matrix ===

  a  b   <-- classified as
 17  3 |  a = bad
  1 36 |  b = good
```

Fig. 3. Efficiency Result

6. CONCLUSION

On running the algorithm and completing the clustering ofthe documents, we got to know that the evaluation methods that need to be used are to be different from that of the previous algorithms. So as mentioned in the previous slides, we built an evaluation measure for the clustering section. Thismethod and also the existing methods were used to evaluate the clustering of the documents. In a previous paper where they used d-trees to develop the clusters F1- the score was primarily used to evaluate, but there were also many other methods that were used along with it. So, with reference to [2],the algorithm that they have used is able to retrieve recordsand data only up to the first level, that is, the parent nodes only. Hence their algorithm uses a d-tree type approach whichis much less complex to do since the number of accesses is very less. In our case, we have tried to access all the existing levels and sublevels to maintain a better clustering method andmore detail.

Comparison between documents. This allows the user to have a better understanding of the type of attributes presentin the data and also helps them understand the variance in the dataset. The algorithm that we have built works with different types of data structures too. Since JSON has the feature to contain arrays, we have added the ability to access the arrays, attributes in the arrays and also the dictionaries in the arrays (records). This allows a wider ability when it comes to the clustering of documents. Also, this brings in new variances between documents that contain different arrays-set and array attributes.

7. REFERENCES

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