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An Unsupervised Approach of Knowledge Discovery from Big Data in Social Network

Mohiuddin Ahmed*

[1]Canberra Institute of Technology, Australia

Abstract

Social network is a common source of big data. It is becoming increasingly difficult to understand what is happening in the network due to the volume. To gain meaningful information or identifying the underlying patterns from social networks, summarization is an useful approach to enhance understanding of the pattern from big data. However, existing clustering and frequent item-set based summarization techniques lack the ability to produce meaningful summary and fails to represent the underlying data pattern. In this paper, the effectiveness co-clustering is explored to create meaningful summary of social network data such as Twitter. Experimental results show that, using co-clustering for creating summary provides significant benefit over the existing techniques.

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1. Introduction

In today's high speed internetworking environment, social networks have become a part of our daily life. Apart from email, social networks are also used heavily for communication. As a result, social networks produce a huge amount of network traffic every single moment. For example, netflow data describes network traffic with a set of records, where each record has different attributes (such as IP, port, bytes transferred etc.). The network analyst has to monitor a huge volume of netflow data. Social media sites i.e. *Twitter* is ranked as one of the ten-most-visited websites worldwide by Alexa's web traffic analysis[1]. Additionally, internet security is an important concern now-a-days since Twitter was compromised for several hours in 2009 due to cyber attack[2]. Thus it is becoming increasingly challenging for the network managers to understand the nature of traffic that is carried in their network [3–8].

A major problem for traffic analysis is to find out a way to extract a concise yet accurate summary of the relevant traffic flows that are present in network traces. There is a significant interest in the data mining and network management communities about the data summarization. Summarization is a common and powerful though often time-consuming approach to analyse large datasets [9–11]. In the scope of this paper, we will consider social network traffic data

1.1. Contributions of the Paper

In this paper, being encouraged by a set of emerging data mining techniques the data summarization problem is solved. Co-clustering is a class of data mining techniques which can find subsets of rows and columns simultaneously [12, 13]. We utilize this advantage of co-clustering for data summarization and representing the original data in a meaningful way. We used the *Twitter* network traffic instances from UCI machine learning repository[14] and show that our proposed approach is capable of creating a better summary than the existing techniques, such as clustering, frequent itemset.

*Corresponding author. Email: m.ahmed.au@ieee.org

1.2. Roadmap

The roadmap of this paper is as follows. In Section 2, we discuss the existing techniques of data summarization with example and highlight the drawbacks. Section 3 includes the basics of co-clustering algorithms used in this paper followed by our proposed approach in Section 4. Experimental results are included in Section 5 and we conclude the paper in Section 6.

2. Background and Related Works

Summarization can be viewed as reducing a given set of transactions into a smaller set of patterns while retaining the maximum possible information. A summary is considered good when it is small but retains enough information about the assigned data. Definition of a summary can be given as follows:

A summary S of a set of transaction T is a set of individual summaries (S_1, S_2, S_l) such that (i) each S_j represents a subset of T and (ii) every transaction Ti ∈ T is represented by at least one $S_j \in$ S. Each individual summary S_j essentially covers a set of transactions. In the summary S, these transactions are replaced by the individual summary that covers them.

Most frequently used metrics for evaluating summary are compaction gain and information loss. Compaction gain signifies the amount of reduction done in the transformation from actual data to a summary. Information loss is defined as the total amount of information missing over all original data. In this paper, we will also investigate whether summarization can represent the underlying pattern or not. Clustering, which groups together similar data instances is used to create summary by considering the centroids of each cluster as the representatives. However, the underlying data pattern can be hardly represented using this method. Frequent itemset based summarization fails to portray all the attributes of the data and hence incurs information loss.

For data summarization, clustering algorithms such as *k-means* have been used the following basic definition.

Definition 1: ‘*Once the dataset is clustered, the cluster centroids are used to form the summary of the original dataset*’.

The basic *k-means* algorithm has been widely used for this type of semantic summarization [15–18]. However, we give an example here to demonstrate how *k-means* algorithm fails to provide an appropriate summary.

We took a sample *Twitter* data[14] and when the centroid is calculated it is seen that the summary produced rarely represent the original data. Table 2 displays the summary of the dataset of Table 1 according to the **Definition 1** stated above. Here the summary is the mean or the average of the data instances which is not an actual member of the cluster and the summary hardly represents the original dataset. Additionally, the categorical data cannot be handled using the **Definition 1**. Also the number of clusters needs to be provided as an input of the algorithm and without having previous knowledge on the dataset, finding the optimal number of cluster is hardly possible.

Table 1. Sample network traffic from Twitter data*

NCD-0	NCD-1	NCD-2	NCD-3	NCD-4	NCD-5	NCD-6
889	939	960	805	805	1143	1121
542	473	504	626	647	795	832
92	99	196	100	184	79	162
90	87	92	344	184	848	184
169	98	101	90	96	95	185
775	765	935	806	912	1095	1198
469	1092	332	354	357	676	1189
818	693	756	1099	877	871	1409
832	628	898	944	993	983	1037
920	1071	833	662	851	1096	1067

*For simplicity and space, we include only one class of attributes out of 11 different types. This table contains the data from number of created discussions(NCD)

Table 2. Summary of the dataset in Table 1 according to **Definition 1**

NCD-0	NCD-1	NCD-2	NCD-3	NCD-4	NCD-5	NCD-6
559.6	594.5	560.7	583	590.6	768.1	838.4

Next, we discuss about the feature-wise intersection used to define a summary [19, 20]. The most recent paper on network traffic monitoring [20], which is a modified version of [19], characterized a summary as a compressed version of a set of given transactions. According to Chandola et al [19], the definition of a summary as follows-

Definition 2: ‘*A summary S of a set of transactions T, is a set of individual summaries $S_1, S_2, ...S_l$ such that (i) each S_j represents a subset of T and (ii)every transaction $T_i \in T$ is represented by at least one $S_j \in S$. An individual summary will be treated as a feature-wise intersection of all transactions covered by it, i.e., if S_j covers $T_1, T_2, ..., T_k$, then $S_j = \bigcap_{i=1}^{k} T_i$.*’

Following this **Definition 2**, Table 2 displays the summary of the dataset in Table 1. Here it is visible that, none of the attributes are present and might not help a network manager to get the idea of the network. Clearly, the summary lacks meaningful information. The data instances might have different values (see Table 1) and in this case, feature-wise intersection resulted in a meaningless summary (Table 3). In this scenario, we are motivated to apply a new summarization technique for social network data using co-clustering and a new algorithm to address the problems of the existing definitions (next section).

Table 3. Summary of the dataset in Table I according to **Definition 2**

NCD-0	NCD-1	NCD-2	NCD-3	NCD-4	NCD-5	NCD-6
*	*	*	*	*	*	*

3. Co-clustering

Co-clustering can be simply considered as a simultaneous clustering of both rows and columns. Co-clustering can produce a set of column clusters of the original columns and a set of row clusters of original row instances [23–26]. Like other clustering algorithms, co-clustering also defines a clustering criterion and then optimizes it. In other words, co-clustering finds out the subsets of rows and columns of a dataset simultaneously using a specified criterion. A conceptual view of co-clustering is shown in Figure 1 and it can be clearly seen that co-clustering is able to create a cluster for the snake and insect in two different clusters. Next, two different types of co-clustering is briefly discussed.

- **Block Co-clustering:** Govaert and Nadif et al[26] proposed a probabilistic framework for model based co-clustering. The backbone of their proposed block co-clustering is latent block model. This model is based on the conditional independence and independent latent variables.

- **Information Theoretic Co-clustering:** Banerjee et al[25] proposed information theoretic co-clustering based on *Bregman Divergence*. It tries to minimize the information loss in the approximation of a data matrix, in terms of a predefined bregman divergence function. For a given co-clustering and a matrix approximation scheme, a class of random variables which store the characteristics of data matrix is defined. The objective function tries to minimize the information loss on the approximation for a co-clustering.

4. Proposed Summarization Algorithm

In this section, we discuss our proposed algorithm for summarizing social network data. Our proposed algorithm is based on the co-clustering techniques discussed in the previous section. Algorithm 1 presents the step by step and we discuss individual steps as follows.

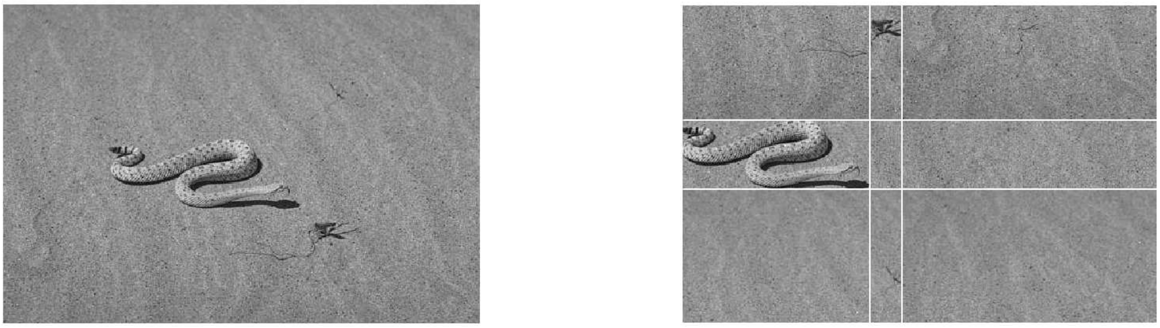
The SSC algorithm takes the dataset, row,column attributes and the number of rows,column for the desired co-clustering. For the pre-processing step, a general practise is to normalize the data or linearly scale the data in a specified range. Then the co-clustering is applied on the dataset as per the number of rows and columns as other input parameter. Here in this paper, we have used two types of co-clustering algorithms discussed in previous section. Both of these algorithms require the number of rows and columns as compulsory input. The number of rows and columns reflect the underlying data pattern and provided by the domain experts. For example, in social network datasets, the columns are composed of different features but there are group of features which are similar and can be considered as a representative of that group.

ALGORITHM 1: SSC: Social Network Data Summarization using Co-Clustering

Input : D, Dataset;
R, Row Attributes;
C, Column Attributes
r, number of rows;
c, number of columns.
Output: Co-clustered data and the summary, S
Begin
Preprocess(D)
Co-cluster(D,r,c)
for *each column cluster, i = 1:c* **do**
    Extract the column index, c_{index}
    $S_c(i)$ = match(C, c_{index})
end
for *each row cluster, i = 1:r* **do**
    Extract the row index, r_{index}
    $S_r(i)$ = match(R, r_{index})
end
Column Summary = *Union i=1....c* $S_c(i)$
Row Summary = *Union i=1....r* $S_r(i)$
Final Summary, $S = \{S_r(i), S_c(i)\}$
End

The same assumption complies with the row instances, for simple understanding, we can think of a dataset with normal and abnormal data instances. Once the co-clustering technique produces the clusters, the index of column and row clusters are extracted. In the next step, the extracted index are matched with the original row and column attribute information provided as input to this algorithm.

The final summary includes information about the summary of the complete dataset. From column summary, it will be visible that whether the underlying feature groups in the original data can be captured by the column clusters or not. Simultaneously, the row clusters will reflect whether the latent pattern in the data is detected or not. Most importantly the produced



(a. Original data) (b. Co-clustered data)

Figure 1. Conceptual view of co-clustering, adapted from [21]

summary contains information about the entire dataset and provides a clear understanding of the data.

5. Analysis of the Results

Our experimental data is based on the *Twitter* and *Tom's Hardware* data from UCI Machine Learning Repository[14]. *Twitter* data contains 140707 data instances and 77 attributes. Tom's Hardware data has 7905 instances and 96 attributes. The underlying data pattern is depicted in Table 4 and 5 respectively[1].

We have used the block co-clustering R package[21] and information theoretic co-clustering from this source[22]. For the row and column input, it is clear from the data pattern that, *Twitter* dataset requires (row=2,column=11) and *Tom's Hardware* dataset requires (row=2, column=12) as input. The following tables display the summaries produced by two particular co-clustering applied on two different datasets discussed above.

Here it is visible that, co-clustering techniques can be able to provide a clear idea about the dataset. Although the *k-means* algorithm seems to be identical but it cannot reduce the column size. The summary dataset size according to *k-means* is (row=2×column=77) 154, whereas the co-clustering methods produce summary of size (row=2×column=11) 22. In this regard, frequent itemset[19, 20] based summarization techniques are not comparable with the proposed techniques because they follow a different set input parameters. Interestingly, our proposed method is better than other techniques due to the fact that, it can cover the whole dataset instead of providing a partial information about the dataset.

[1]For space scarcity, the attribute group names are abridged and each of the attributes has 7 similar features.

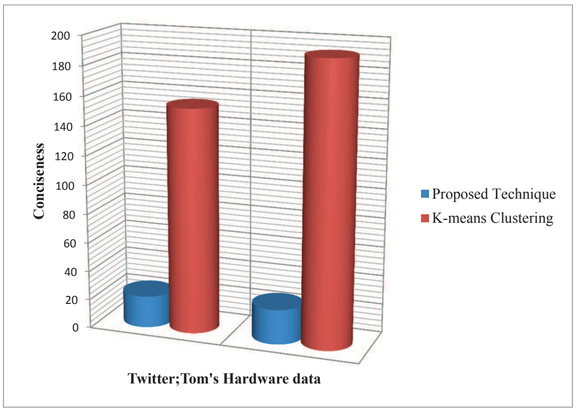


Figure 2. Conciseness Comparison

Table 6,7 also displays the summaries using both co-clustering and regular clustering. Figure 2 displays the conciseness of the summaries produced by co-clustering and regular clustering[9] and it is clear that, co-clustering can produce concise summary without losing information rather the summaries are more meaningful than the existing techniques. The summaries produced by existing techniques are shown in section 2, are representing a part of the dataset and less meaningful than our proposed technique. Our proposed technique takes the benefit of co-clustering to create meaningful summary which represent the whole dataset and identifies the underlying pattern.

5.1. Bipartite Graph to Represent Summary

Interestingly, there is a hidden data structure in co-clustering as well as the produced summaries. The summaries produced by co-clustering reflects the properties of complete bipartite graph. For example, the produced row clusters are all connected to all the column clusters and vice versa. This characteristic simplifies the data summarization using co-clustering far more. Figure 3 shows the complete bi-partite graph

Table 4. Data pattern of Twitter data[14]

	NCD	AI	AS(NA)	BL	NAC	AS(NAC)	CS	AT	NA	ADL	NAD
Buzz- 27775	√	√	√	√	√	√	√	√	√	√	√
No Buzz- 112932	√	√	√	√	√	√	√	√	√	√	√

Table 5. Data pattern of Tom's Hardware data[14]

	NCD	BL	NAD	AI	NAC	ND	CS	AT	NA	ADL	AS(NA)	AS(NAC)
Buzz- 4860	√	√	√	√	√	√	√	√	√	√	√	√
No Buzz- 3045	√	√	√	√	√	√	√	√	√	√	√	√

Table 6. Summary of Twitter data[14] using Different Methods

	Block		Information Theoretic		K-means	
	Buzz	No Buzz	Buzz	No Buzz	Buzz	No Buzz
Cluster-1	3318	79593	21943	112923	5070	112929
Cluster-2	24457	33339	5832	9	22705	3

Table 7. Summary of Tom's Hardware data[14] using Different Methods

	Block		Information Theoretic		K-means	
	Buzz	No Buzz	Buzz	No Buzz	Buzz	No Buzz
Cluster-1	4680	3045	644	771	4687	3045
Cluster-2	180	0	4216	2268	173	0

for the *Twitter* data. The produced two row clusters are all connected with the eleven column clusters. Which indicates, the whole dataset is taken into consideration for the summarization process and identifying the patterns.

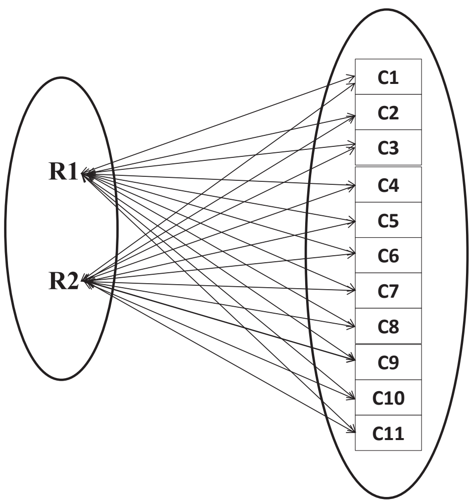


Figure 3. Summary representation using bipartite graph

6. Conclusion

In this paper, we have utilized the power of co-clustering to simultaneously cluster rows and columns of a dataset to create meaningful summary. We have explained in our results that, our proposed technique cover the whole dataset for creating summary and can detect the underlying data pattern. Existing summarization techniques are not able to cover the whole dataset and cannot provide the underlying data pattern.

We have experimented with the social network data and have shown that, our proposed technique is able to create concise summary yet identify the underlying data pattern encompassing the whole dataset. We also discussed the drawbacks of the existing techniques and our future work will include the application of co-clustering in other domain as well as network traffic analysis to efficiently detect the anomalies from the summary.

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