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Summarization - Compressing Data into an Informative Representation

Varun Chandola and Vipin Kumar

Department of Computer Science, University of Minnesota, MN, USA

Abstract. In this paper, we formulate the problem of summarization of a dataset of transactions with categorical attributes as an optimization problem involving two objective functions - compaction gain and information loss. We propose metrics to characterize the output of any summarization algorithm. We investigate two approaches to address this problem. The first approach is an adaptation of clustering and the second approach makes use of frequent itemsets from the association analysis domain. We illustrate one application of summarization in the field of network data where we show how our technique can be effectively used to summarize network traffic into a compact but meaningful representation. Specifically, we evaluate our proposed algorithms on the 1998 DARPA Off-line Intrusion Detection Evaluation data and network data generated by SKAION Corp for the ARDA information assurance program.

Keywords: Summarization; Frequent Itemsets; Categorical Attributes

1. Introduction

Summarization is a key data mining concept which involves techniques for finding a compact description of a dataset. Simple summarization methods such as tabulating the mean and standard deviations are often applied for data analysis, data visualization and automated report generation. Clustering [13, 23] is another data mining technique that is often used to summarize large datasets. For example, centroids of document clusters derived for a collection of text documents [21] can provide a good indication of the topics being covered in the collection. The clustering based approach is effective in domains where the features are continuous or asymmetric binary [23, 10], and hence cluster centroids are a meaningful description of the clusters. However, if the data has categorical

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Feature	Type	Possible Values
Source IP	Categorical	2^{32}
Source Port	Categorical	2^{16}
Destination IP	Categorical	2^{32}
Destination Port	Categorical	2^{16}
Protocol	Categorical	≤ 10
Number of Packets	Continuous	1 - ∞
Number of Bytes	Continuous	1 - ∞
TCP Flags	Categorical	≤ 10

Table 1. Different features for netflow data

attributes, then the standard methods for computing a cluster centroid are not applicable and hence clustering cannot directly be applied for summarization[1]. One such application is in the analysis of netflow data to detect cyber attacks.

Netflow data is a set of records that describe network traffic, where each record has different features such as the IPs and ports involved, packets and bytes transferred (see Table 1). An important characteristic of netflow data is that it has a mix of categorical and continuous features. The volume of netflow data which a network analyst has to monitor is huge. For example, on a typical day at the University of Minnesota, more than one million flows are collected in every 10 minute window. Manual monitoring of this data is impossible and motivates the need for data mining techniques. Anomaly detection systems [9, 17, 4, 22] can be used to score these flows, and the analyst typically looks at only the most anomalous flows to identify attacks or other undesirable behavior. In a typical window of data being analyzed, there are often several hundreds or thousands of highly ranked flows that require the analyst's attention. But due to the limited time available, analysts look at only the first few pages of results that cover the top few dozen most anomalous flows. If many of these most anomalous flows can be summarized into a small representation, then the analyst can analyze a much larger set of anomalies than is otherwise possible. For example, Table 2 shows 17 flows which were ranked as most suspicious by the MINDS Anomaly Detection Module [9] for the network traffic analyzed on January 26, 2003 (48 hours after the *Slammer Worm* hit the Internet) for a 10 minute window that contained 1.8 million flows. These flows are involved in three anomalous activities - *slammer worm* related traffic on port 1434, flows associated with a *half-life* game server on port 27016 and *ping scans* of the inside network by an external host on port 2048. If the dataset shown in Table 2 can be automatically summarized into the form shown in Table 3 (the last column has been removed since all the transactions contained the same value for it in Table 2), then the analyst can look at only 3 lines to get a sense of what is happening in 17 flows. Table 3 shows the output summary for this dataset generated by an application of our proposed scheme. We see that every flow is represented in the summary. The first summary S_1 represents flows $\{T_1$-T_{10},T_{14}-$T_{16}\}$ which correspond to the *slammer worm* traffic coming from a single external host and targeting several internal hosts. The second summary S_2 represents flows $\{T_{12}$,$T_{13}\}$ which are the

[1] Traditionally, a centroid is defined as the average of the value of each attribute over all transactions. If a categorical attribute has different values (say red, blue, green) for three different transactions in the cluster, then it does not make sense to take an average of the values. Although it is possible to replace a categorical attribute with an asymmetric binary attribute for each value taken by the attribute, such methods do not work well when the attribute can take a large number of values, as in the netflow data – see Table 1.

	Score	srcIP	sPort	dstIP	dPort	prot	pkts	bytes
T_1	37675	63.150.X.253	1161	128.101.X.29	1434	udp	[0,2)	[0,1829)
T_2	26677	63.150.X.253	1161	160.94.X.134	1434	udp	[0,2)	[0,1829)
T_3	24324	63.150.X.253	1161	128.101.X.185	1434	udp	[0,2)	[0,1829)
T_4	21169	63.150.X.253	1161	160.94.X.71	1434	udp	[0,2)	[0,1829)
T_5	19525	63.150.X.253	1161	160.94.X.19	1434	udp	[0,2)	[0,1829)
T_6	19235	63.150.X.253	1161	160.94.X.80	1434	udp	[0,2)	[0,1829)
T_7	17679	63.150.X.253	1161	160.94.X.220	1434	udp	[0,2)	[0,1829)
T_8	8184	63.150.X.253	1161	128.101.X.108	1434	udp	[0,2)	[0,1829)
T_9	7143	63.150.X.253	1161	128.101.X.223	1434	udp	[0,2)	[0,1829)
T_{10}	5139	63.150.X.253	1161	128.101.X.142	1434	udp	[0,2)	[0,1829)
T_{11}	4048	142.150.Y.101	0	128.101.X.142	2048	icmp	[2,4)	[0,1829)
T_{12}	4008	200.250.Z.20	27016	128.101.X.116	4629	udp	[2,4)	[0,1829)
T_{13}	3657	202.175.Z.237	27016	128.101.X.116	4148	udp	[2,4)	[0,1829)
T_{14}	3451	63.150.X.253	1161	128.101.X.62	1434	udp	[0,2)	[0,1829)
T_{15}	3328	63.150.X.253	1161	160.94.X.223	1434	udp	[0,2)	[0,1829)
T_{16}	2796	63.150.X.253	1161	128.101.X.241	1434	udp	[0,2)	[0,1829)
T_{17}	2694	142.150.Y.101	0	128.101.X.168	2048	icmp	[2,4)	[0,1829)

Table 2. Top 17 anomalous flows as scored by the anomaly detection module of the MINDS system for the network data collected on January 26, 2003 at the University of Minnesota (48 hours after the *Slammer Worm* hit the Internet). The third octet of IPs is anonymized for privacy preservation.

	Size	Score	srcIP	sPort	dstIP	dPort	prot	pkts
S_1	13	15102	63.150.X.253	1161	***	1434	udp	[0,2)
S_2	2	3833	***	27016	128.101.X.116	***	udp	[2,4)
S_3	2	3371	142.150.Y.101	0	***	2048	icmp	[2,4)

Table 3. Summarization output for the dataset in Table 2. The last column has been removed since all the transactions contained the same value for it in the original dataset.

connections made to *half-life* game servers made by an internal host. The third summary, S_3 represents flows $\{T_{11},T_{17}\}$ which correspond to a *ping scan* by the external host. In general, such summarization has the potential to reduce the size of the data by several orders of magnitude.

In this paper, we address the problem of summarization of data sets that have categorical features. We view summarization as a transformation from a given dataset to a smaller set of individual summaries with an objective of retaining the maximum information content. A fundamental requirement is that *every data item should be represented in the summary.*

1.1. Contributions

Our contributions in this paper are as follows –

- We formulate the problem of summarization of transactions that contain categorical data, as a dual-optimization problem and characterize a good summary using two metrics – *compaction gain* and *information loss*. Compaction gain signifies the amount of reduction done in the transformation from the actual data to a summary. Information loss is defined as the total amount of information missing over all original data transactions in the summary.
- We investigate two approaches to address this problem. The first approach is an adaptation of clustering and the second approach makes use of frequent itemsets from the association analysis domain [3].
- We present an optimal but computationally infeasible algorithm to generate the best summary for a set of transactions in terms of the proposed metrics.

	src IP	sPort	dst IP	dPort	pro	flags	packets	bytes
T_1	12.190.84.122	32178	100.10.20.4	80	tcp	—APRS-	[2,20]	[504,1200]
T_2	88.34.224.2	51989	100.10.20.4	80	tcp	—APRS-	[2,20]	[220,500]
T_3	12.190.19.23	2234	100.10.20.4	80	tcp	—APRS-	[2,20]	[220,500]
T_4	98.198.66.23	27643	100.10.20.4	80	tcp	—APRS-	[2,20]	[42,200]
T_5	192.168.22.4	5002	100.10.20.3	21	tcp	—A-RSF	[2,20]	[42,200]
T_6	192.168.22.4	5001	100.10.20.3	21	tcp	—A-RS-	[40,68]	[220,500]
T_7	67.118.25.23	44532	100.10.20.3	21	tcp	—A-RSF	[40,68]	[42,200]
T_8	192.168.22.4	2765	100.10.20.4	113	tcp	—APRS-	[2,20]	[504,1200]

Table 4. A synthetic dataset of network flows.

We also present a computationally feasible heuristic-based algorithm and investigate different heuristics which can be used to generate an approximately good summary for a given set of transactions.

– We illustrate one application of summarization in the field of network data where we show how our technique can be effectively used to summarize network traffic into a compact but meaningful representation. Specifically, we evaluate our proposed algorithms on the 1998 DARPA Off-line Intrusion Detection Evaluation data [15] and network data generated by SKAION Corp for the ARDA information assurance program [1].

2. Characterizing a Summary

Summarization can be viewed as compressing a given set of transactions into a smaller set of patterns while retaining the maximum possible information. A trivial summary for a set of transactions would be itself. The information loss here is zero but there is no compaction. Another trivial summary would be the empty set ϵ, which represents all the transactions. In this case the gain in compaction is maximum but the summary has no information content. A good summary is one which is small but still retains enough information about the data as a whole and also for each transaction.

We are given a set of n categorical features $F = \{F_1, F_2, \ldots, F_n\}$ and an associated weight vector W such that each $W_i \in W$ represents the weight of the feature $F_i \in F$. A set of transactions T, such that $|T| = m$, is defined using these features, and each $T_i \in T$ has a specific value for each of the n features. Formally, a summary of a set of transactions can be defined as follows:

Definition 1. (**Summary**) A summary S of a set of transactions T, is a set of individual summaries $\{S_1, S_2, \ldots, S_l\}$ 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 $S_j \in S$.

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. As we mentioned before, computing the centroid for data with categorical attributes is not possible. For such data, a feature-wise intersection of all transactions is a more appropriate description of an individual summary. Hence, from now on, an individual summary will be treated as a feature-wise intersection of all transactions covered by it, i.e., if S_j covers $\{T_1, T_2, \ldots, T_k\}$, then $S_j = \bigcap_{i=1}^{k} T_i$. For the sake of illustration let us consider the sample netflow data given in Table 4. The dataset shown is a set of 8 transactions that are described by 6 categorical features and 2 continuous features (see Table 1). Let

	src IP	sPort	dst IP	dPort	pro	flags	packets	bytes
S_1	*.*.*.*	***	100.10.20.4	***	tcp	—APRS-	[2,20]	***
S_2	*.*.*.*	***	100.10.20.3	21	tcp	***	***	***
S_3	192.168.22.4	2765	100.10.20.4	113	tcp	—APRS-	[2,20]	[504,1200]

Table 5. A possible summary for the dataset shown above.

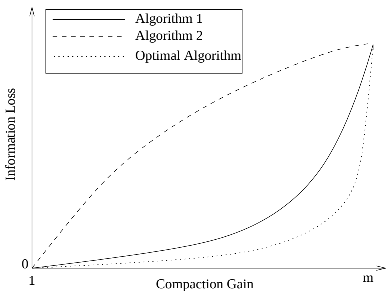

Fig. 1. ICC Curve for summarization algorithms

all the features have equal weight of $\frac{1}{8}$. One summary for this dataset is shown in Table 5 as a set of 3 individual summaries. The individual summary S_1 covers transactions $\{T_1,T_2,T_3,T_4,T_8\}$, S_2 covers transactions $\{T_5,T_6,T_7\}$ and S_3 covers only one transaction, T_8.

To assess the quality of a summary S of a set of transactions T, we define following metrics -

Definition 2. (**Compaction Gain for a Summary**) Compaction Gain = $\frac{m}{l}$. (Recall that $m = |T|$ and $l = |S|$.)

For the dataset in Table 4 and the summary in Table 5, *Compaction Gain for S* $= \frac{8}{3}$.

Definition 3. (**Information Loss for a transaction represented by an individual summary**) For a given transaction $T_i \in T$ and an individual summary $S_j \in S$ that covers T_i, $loss_{ij} = \sum_{q=1}^{n} W_q * b_q$, where, $b_q = 1$ if $T_{iq} \notin S_j$ and 0 otherwise.

The loss incurred if a transaction is represented by an individual summary will be the weighted sum of all features that are absent in the individual summary.

Definition 4. (**Best Individual Summary for a transaction**) For a given transaction $T_i \in T$, a best individual summary $S_j \in S$ is the one for which $loss_{ij}$ is minimum.

The total information loss for a summary is the aggregate of the information lost for every transaction with respect to its best individual summary.

For the dataset in Table 4 and its summary shown in Table 5, transactions T_1-T_4 are best covered by individual summary S_1 and each has an information loss of $\frac{4}{8}$. Transactions T_5-T_7 are best covered by individual summary S_2 and each has an information loss of $\frac{5}{8}$. T_8 is represented by S_1 and S_3. For T_8 and S_1, information loss $= 4 \times \frac{1}{8} = \frac{1}{2}$, since there are 4 features absent in S_1. For T_8 and S_3, information loss = 0 since there are no features absent in S_3. Hence the best individual summary for T_8 will be S_3. Thus, we get that *Information Loss for S* $= \frac{4}{8} \times 4 + \frac{5}{8} \times 3 + 0 = \frac{31}{8} = 3.875$.

Clustering-based Algorithm
Input: T: a transaction data set.
W: a set of weights for the features.
l: size of final summary
Output : S: the final summary.

Variables :C: clusters of T.

Method:
1. Initialize $S = \{\}$
2. Run clustering T to obtain a set of l clusters, $\bar{C}$.
3. **for** each $\bar{C}_i \in \bar{C}$
4. $S_i = \bigcap_{j=1}^{m} C_{ij}$
5. **endfor**
6. **End**

Fig. 2. The Clustering-based Algorithm

It is to be noted that the characteristics, *compaction gain* and *information loss*, follow an optimality tradeoff curve as shown in Figure 1 such that increasing the compaction results in increase of information loss. We denote this curve as ICC (*Information-loss Compression-gain Characteristic*) curve.

The ICC curve is a good indicator of the performance of a summarization algorithm. The beginning and the end of the curve are fixed by the two trivial solutions discussed earlier. For any summarization algorithm, it is desirable that the area under its ICC curve be minimal. It can be observed that getting an optimal curve as shown in Figure 1 involves searching for a solution in exponential space and hence not feasible. But a good algorithm should be close enough to the optimal curve like 1 and not like 2 in the figure shown.

As the ICC curve indicates, there is no global maxima for this dual-optimization problem since it involves two orthogonal objective functions. So a typical objective of a summarization algorithm would be - *for a given level of compaction find a summary with the lowest possible information loss.*

3. Summarization Using Clustering

In this section, we present a direct application of clustering to obtain a summary for a given set of transactions with categorical attributes. This simple algorithm involves clustering of the data using any standard clustering algorithm and then replacing each cluster with a representation as described earlier using feature-wise intersection of all transactions in that cluster. The weights W are used to calculate the distance between two data transactions in the clustering algorithm. Thus, if $\bar{C}$ is a set of clusters obtained from a set of transactions T by clustering, then each cluster produces an individual summary which is essentially the set of feature-value pairs which are present in all transactions in that cluster. The number of clusters here determine the compaction gain for the summary.

Figure 2 gives the clustering based algorithm. Step 2 generates l clusters, while step 3 and 4 generate the summary description for each of the individ-

	src IP	sPort	dst IP	dPort	protocol	flags	packets	bytes
C_1	*.*.*.*	***	100.10.20.4	***	tcp	—APRS-	[2,20]	***
C_2	*.*.*.*	***	100.10.20.3	21	tcp	***	***	***

Table 6. A summary obtained for the dataset in Table 4 using the clustering based algorithm

	src IP	sPort	dst IP	dPort	protocol	flags	packets	bytes
T_9	12.190.84.122	32178	100.10.20.10	53	udp	———	[25,60]	[2200,5000]

Table 7. An outlying transaction T_9 added to the data set in Table 4

ual clusters. For illustration consider again the sample dataset of 8 transactions in Table 4. Let clustering generate two clusters for this dataset – $C_1 = \{T_1,T_2,T_3,T_4,T_8\}$ and $C_2 = \{T_5,T_6,T_7\}$. Table 6 shows a summary obtained using the clustering based algorithm.

The clustering based approach works well in representing the frequent modes of behavior in the data because they are captured well by the clusters. However, this approach performs poorly when the data has outliers and less frequent patterns. This happens because the outlying transactions are forced to belong to some cluster. If a cluster has even a single transaction which is different from other cluster members, it degrades the description of the cluster in the summary. For example, let us assume that another transaction T_9 as shown in Table 7 is added to the dataset shown in Table 4 and clustering assigns it to cluster C_1.

On adding T_9 to C_1, the summary generated from C_1 will be empty. The presence of this outlying transaction makes the summary description very lossy in terms of information content. Thus this approach represents outliers very poorly, which is not desirable in applications such as network intrusion detection and fraud detection where such outliers can be of special interest.

4. An Optimal Summarization Algorithm

In this section we propose an exhaustive search algorithm (shown in Figure 3) which is guaranteed to generate an optimal summary of given size l for a given set of transactions, T. The first step of this algorithm involves generating the powerset of T (= all possible subsets of T), denoted by $\mathscr{C}$. The size of $\mathscr{C}$ will be $2^{|T|}$. The second step involves searching all possible subsets of $\mathscr{C}$ ($2^{2^{|T|}}$ subsets) to select a subset, S which has following properties

Property 1.

(1) $|S| = l$, the size of this subset is equal to desired compaction level

(2) The subset S covers all transactions in T (a set cover of T)

(3) The total information loss for S with respect to T is minimum over all other subsets of T which satisfy the properties 1 and 2

We denote the optimal summary generated by the algorithm in Figure 3 by $\mathscr{S}$. The optimal algorithm follows the optimal ICC curve as shown in Figure 1.

Optimal Algorithm
Input: T: a transaction data set.
W: a set of weights for each feature.
l: size of final summary
Output : S: the final summary.

Method:

```
1.  Generate 𝒞 = power set of T
2.  Let current_min_loss = inf
3.  Let S = {}
4.  Foreach 𝒞_i ∈ 𝒞
5.      If |𝒞_i| = l And Information Loss for 𝒞_i < current_min_loss
6.          current_min_loss = Information Loss for 𝒞_i
7.          S = 𝒞_i
8.      End If
9.  End Foreach
10. Return S
11. End
```

Fig. 3. The Optimal Algorithm

5. A Two-step Approach to Summarization using Frequent Itemsets

The optimal algorithm presented in Section 4 requires searching in a $2^{2^{|T|}}$ space (for 4 transactions it would require searching a set of 65,536 subsets), which makes it computationally infeasible even for very small data sets. In this section we propose a methodology which simplifies each of the two steps of the optimal algorithm to make them computationally more efficient. We first present the following lemma.

Lemma 1. Any subset of T belonging to the optimal summary, $\mathscr{S}$ must belong to C_c, where C_c denotes a set containing all *closed* frequent itemsets[2] generated with a support threshold of 2 and T itself.

Proof. This can be easily proved by contradiction. Suppose the optimal summary contains a subset $S_i \in \mathscr{C}$ - C_c. Thus there will be a subset $S_j \in C_c$ which "closes" S_i, which means $S_j \supset S_i$ and $support(S_i) = support(S_j)$. We can replace S_i with S_j in $\mathscr{S}$ to obtain another summary, $\mathscr{S}'$ such that all the transactions represented by S_i in $\mathscr{S}$ are represented by S_j in $\mathscr{S}'$. Since $S_j \supset S_i$, the information loss for these transactions will be lower in $\mathscr{S}'$. Thus $\mathscr{S}'$ will have lower information loss than $\mathscr{S}$ for the same compaction which is not possible since $\mathscr{S}$ is an optimal summary. □

We modify the Step 1 of optimal algorithm in Figure 3 and replace $\mathscr{C}$ with C_c. The result from Lemma 1 ensures that we can still obtain the optimal summary from the reduced candidate set. But to obtain an optimal solution we still

[2] An itemset X is a **closed itemset** if there exists no proper superset $X' \supset X$ such that $support(X') = support(X)$.

need to search from the powerset of C_c, which is still computationally infeasible. Higher values of the support threshold can be used to further prune the number of possible candidates, but this can impact the quality of the summaries obtained.

We replace the Step 2 of optimal algorithm with a *greedy search* which avoids the exponential search by greedily searching for a good solution. This does not guarantee the optimal summary but tries to follow the optimal ICC curve (refer to Figure 1). The output (a subset of C_c) of Step 2 of our proposed algorithms satisfiy Property 1.1 and Property 1.2 mentioned in Section 4 but is not guaranteed to satisfy Property 1.3.

The selection of a subset of C_c such that its size satisfies the desired compaction level while the information loss associated with this subset is approximately minimal can be approached in two ways.

- The first approach works in a *top-down* fashion where every transaction belonging to T selects a "best" candidate for itself (based on a heuristic based function which will be described in later in this section). The union of all such candidates is the summary for T.
- The second approach works in a *bottom-up* fashion by starting with T as the initial summary and choosing a "best" candidate at every step and adding it to the summary. The individual summaries that are covered by the chosen candidates are replaced, thereby causing compaction.

In this paper we will discuss only the *bottom-up* approach for summarization. An algorithm based on the *top-down* approach is presented in an extended technical report [8]. Both of these approaches build a summary in an iterative and incremental fashion, starting from the original set of transactions T as the summary. Thus from the ICC curve perspective, they start at the left hand corner (*compaction=1,loss=0*). At each iteration the compaction gain increases along with the information loss. Each iteration makes the current summary smaller by bringing in one or more candidates into the current summary.

6. A Bottom-up Approach to Summarization - The BUS Algorithm

The main idea behind the BUS algorithm is to incrementally select best candidates from the candidate set such that at each step, for a certain gain in compaction, minimum information loss is incurred. The definition of a "best" candidate is based on a heuristic decision and can be defined in several different ways as we will describe later.

Figure 4 presents a generic version of BUS. Line 1 involves generation of all closed frequent itemsets of T. As mentioned earlier, choosing a support threshold of 2 transactions while generating the frequent itemsets as well as the transactions themselves ensures that we capture patterns of every possible size. The rest of the algorithm works in an iterative mode until a summary of desired compaction level l is obtained. In each iteration a candidate from C_c is chosen using the routine *select_best*. We have investigated several heuristic versions of *select_best* which will be described later. The general underlying principle for designing a *select_best* routine is to ensure that the selected candidate incurs very

BUS Algorithm
Input: T: a transaction data set.
W: a set of weights for each feature.
l: size of final summary
Variables : S_c: current summary
Output : S: the final summary.

Method:
Generate $C_c = \{$All closed frequent itemsets of $T\} + T$
While ($|S_c|$!= l)
C_{best} = *select_best*(C_c,S_c,T)
$S_c = S_c$ - {Summaries in S_c covered by $C_{best}\} + C_{best}$
End While
$S = S_c$
End

Fig. 4. The Generic BUS Algorithm

low information loss while reducing the size of summary. After choosing a best candidate, C_{best}, all individual summaries in current summary which are completely covered[3] by C_{best} are removed and C_{best} is added to the summary (let the new summary be denoted by S'_c).

Thus after each iteration, the size of the summary, S_c is reduced by $size(C_{best})$ - 1, where $size(C_{best})$ denotes the number of individual summaries in S_c completely covered by C_{best}. This is denoted by $gain(C_i, S_c)$ and represents the compaction gain achieved by choosing candidate C_i for a given summary S_c.

For computing the loss incurred by adding C_{best} to the current summary (and replacing the summaries covered by C_{best}), we need to consider the transactions which will consider C_{best} as their *best individual summary* (refer to Definition 4) in the new summary. For all such transactions, the difference in the loss when they were represented in S_c by their *best individual summaries* and the loss when they are represented by C_{best} in S'_c is the extra loss incurred in choosing C_{best}. This is denoted by $loss(C_i, S_c)$.

Next we describe four different ways in which function *select_best* can be designed. Each of these approaches make a greedy choice to choose a candidate from the current candidate set C_c which would lead to a *locally optimal solution* but does not ensure that the sequence of these choices will lead to a *globally optimal solution.*

6.1. Method 1

This method (as shown in Figure 5) uses the quantities $gain(C_i, S_c)$ and $loss(C_i, S_c)$, defined above, to score the candidates and choose one to be added to the current summary, S_c. All candidates with $gain(C_i, S_c)$ equal to or less than 1 are

[3] An individual summary is completely covered by a candidate if it is more specific than the candidate

select_best - Method 1
Input: T: a transaction data set.
S_c: current summary.
C_c: candidate set.
Output : C_{best}: best candidate.
Method:
min-loss = minimum($loss(C_i, S_c)$, $\forall C_i \in C_c$ & $gain(C_i, S_c) > 1$)
$C' = \{C_i | C_i \in C_c$ & $gain(C_i, S_c) > 1$ & $loss(C_i, S_c) = min\text{-}loss\}$
$best = argmax_{C_i \in C'}(gain(C_i, S_c))$
return C_{best}
End

Fig. 5. *select_best* - Method 1

ignored (since adding them to the current summary would not result in any compaction gain in the new summary). The remaining candidates are ordered using $loss(C_i, S_c)$. From among the candidates which have lowest value for $loss(C_i, S_c)$, the candidate with highest $gain(C_i, S_c)$ is returned as the *best candidate*.

Thus this approach tries to maintain a very low information loss at each iteration by bringing in the candidates with lowest information loss.

But as mentioned above, the decision to pick up a candidate in this manner might eventually result in a sub-optimal solution. A simple counter-example shown in Figure 6 proves this. Let us consider a simple data set which has four transactions $\{T_1,T_2,T_3,T_4\}$ defined over four attributes $\{a,b,c,d\}$ (each attribute has a unit weight). The aim is to obtain a summary of size 2 for this data set using the BUS algorithm. As shown in the figure, the candidate set C_c contains 9 possible candidates. The BUS algorithm considers the transaction set, T as the initial summary, S_c. The first iteration uses method 1 and (see Figure 7) chooses candidate C_5 as the best candidate, generating a new S_c. The candidate set is rescored as shown in the figure. The next iteration chooses (see Figure 7) C_9 as the best candidate and reduces the size of S_c to 2. The right side table in Figure 7 shows another size 2 summary for the same data set which has a smaller information loss. This shows that this method to score candidates might not result in an optimal solution.

6.2. Method 2

This method (as shown in Figure 9) also uses the quantities $gain(C_i, S_c)$ and $loss(C_i, S_c)$ as in Method 1, but in a different way. All candidates with $gain(C_i, S_c)$ equal to or less than 1 are ignored (since adding them to the current summary would not result in any compaction gain in the new summary). The remaining candidates are ordered using $gain(C_i, S_c)$. From among the candidates which have lowest value for $gain(C_i, S_c)$, the candidate with lowest $loss(C_i, S_c)$ is returned as the *best candidate*.

This method is symmetrically opposite to method 1 and makes use of the symmetry between *information loss* and *compaction gain*. The general idea behind method 2 is that at any iteration, the candidates which cover least number of individual summaries in the current summary S_c, will also incur the lowest possible loss. Similar to method 1, this method for choosing the best candidate

	T
T_1	a_1 b_1 c_1 d_1
T_2	a_1 b_1 c_2 d_2
T_3	a_2 b_2 c_2 d_2
T_4	a_2 b_3 c_2 d_2

		C_c	
		$size(C_i, S_c = T)$	$loss(C_i, S_c = T)$
C_1	$\{T_1\}$	1	0
C_2	$\{T_2\}$	1	0
C_3	$\{T_3\}$	1	0
C_4	$\{T_4\}$	1	0
C_5	$\{T_1,T_2\}$	2	4
C_6	$\{T_2,T_3\}$	2	4
C_7	$\{T_2,T_4\}$	2	4
C_8	$\{T_3,T_4\}$	2	4
C_9	$\{T_2,T_3,T_4\}$	3	6

Fig. 6. *Left* - A simple data set, T with 4 transactions defined over 4 features. Each feature is assumed to have a unit weight. *Right* - The candidate set, C_c with $gain(C_i, S_c)$ and $loss(C_i, S_c)$ defined for current summary, $S_c = T$.

	S_c
C_5	a_1 b_1
T_3	a_2 b_2 c_2 d_2
T_4	a_2 b_3 c_2 d_2

		C_c	
		$size(C_i, S_c)$	$loss(C_i, S_c)$
C_8	$\{T_3,T_4\}$	2	4
C_9	$\{T_2,T_3,T_4\}$	2	4

Fig. 7. *Left* - Current summary, S_c after first iteration. *Right* - The candidate set, C_c after rescoring based on S_c (Showing only the candidates with $gain(C_i, S_c) > 1$).

	S_c
C_5	a_1 b_1
C_8	c_2 d_2

	S'_c
C_1	a_1 b_1 c_1 d_1
C_9	c_2 d_2

Fig. 8. *Left* - Current summary, S_c after second iteration (Size = 2, Information Loss = 8). *Right* - The optimal summary S'_c (Size = 2, Information Loss = 6).

select_best - Method 2
Input: T: a transaction data set.
S_c: current summary.
C_c: candidate set.
Output : C_{best}: best candidate.
Method:
1. *min-gain* = minimum($gain(C_i, S_c)$, $\forall C_i \in C_c$ & $gain(C_i, S_c) > 1$)
2. $C' = \{C_i | C_i \in C_c$ & $gain(C_i, S_c) > 1$ & $gain(C_i, S_c) =$ *min-gain*$\}$
3. $best = argmin_{C_i \in C'}(loss(C_i, S_c))$
4. **return** C_{best}
5. **End**

Fig. 9. *select_best* - Method 2

does not guarantee a globally optimal summary. Consider the transaction data set containing 6 transactions as shown in Figure 10. Figures 11-13 show the working of the BUS algorithm using method 2 to obtain a summary of size 3 for this data set. Figure 13(*right*) shows an alternative summary S'_c, which is of same size as S_c but has a lower information loss.

	T
T_1	a_1 b_1 c_1 d_1
T_2	a_1 b_1 c_2 d_2
T_3	a_2 b_2 c_2 d_2
T_4	a_3 b_3 c_2 d_2
T_5	a_4 b_4 c_2 d_2
T_6	a_4 b_4 c_3 d_3

		C_c	
		$size(C_i, S_c = T)$	$loss(C_i, S_c = T)$
C_1	$\{T_1\}$	1	0
C_2	$\{T_2\}$	1	0
C_3	$\{T_3\}$	1	0
C_4	$\{T_4\}$	1	0
C_5	$\{T_5\}$	1	0
C_6	$\{T_6\}$	1	0
C_7	$\{T_1,T_2\}$	2	4
C_8	$\{T_2,T_3\}$	2	4
C_9	$\{T_2,T_4\}$	2	4
C_{10}	$\{T_2,T_5\}$	2	4
C_{11}	$\{T_3,T_4\}$	2	4
C_{12}	$\{T_3,T_5\}$	2	4
C_{13}	$\{T_4,T_5\}$	2	4
C_{14}	$\{T_5,T_6\}$	2	4
C_{15}	$\{T_2,T_3,T_4\}$	3	6
C_{16}	$\{T_2,T_3,T_5\}$	3	6
C_{17}	$\{T_2,T_4,T_5\}$	3	6
C_{18}	$\{T_3,T_4,T_5\}$	3	6
C_{19}	$\{T_2,T_3,T_4,T_5\}$	4	8

Fig. 10. *Left* - A simple data set, T with 6 transactions defined over 4 features. Each feature is assumed to have a unit weight. *Right* - The candidate set, C_c with $gain(C_i, S_c)$ and $loss(C_i, S_c)$ defined for current summary, $S_c = T$.

	S_c
C_7	a_1 b_1
T_3	a_2 b_2 c_2 d_2
T_4	a_3 b_3 c_2 d_2
T_5	a_4 b_4 c_2 d_2
T_6	a_4 b_4 c_3 d_3

		C_c	
		$size(C_i, S_c)$	$loss(C_i, S_c)$
C_{11}	$\{T_3,T_4\}$	2	4
C_{12}	$\{T_3,T_5\}$	2	4
C_{13}	$\{T_4,T_5\}$	2	4
C_{14}	$\{T_5,T_6\}$	2	4
C_{15}	$\{T_2,T_3,T_4\}$	2	4
C_{16}	$\{T_2,T_3,T_5\}$	2	4
C_{17}	$\{T_2,T_4,T_5\}$	2	4
C_{18}	$\{T_3,T_4,T_5\}$	3	6
C_{19}	$\{T_2,T_3,T_4,T_5\}$	3	6

Fig. 11. *Left* - Current summary, S_c after first iteration. *Right* - The candidate set, C_c after rescoring based on S_c (Showing only the candidates with $gain(C_i, S_c) > 1$).

	S_c
C_7	a_1 b_1
C_{11}	c_2 d_2
T_5	a_4 b_4 c_2 d_2
T_6	a_4 b_4 c_3 d_3

		C_c	
		$size(C_i, S_c)$	$loss(C_i, S_c)$
C_{14}	$\{T_5,T_6\}$	2	4
C_{18}	$\{T_3,T_4,T_5\}$	2	2
C_{19}	$\{T_2,T_3,T_4,T_5\}$	2	2

Fig. 12. *Left* - Current summary, S_c after second iteration. *Right* - The candidate set, C_c after rescoring based on S_c (Showing only the candidates with $gain(C_i, S_c) > 1$).

	S_c
C_7	a_1 b_1
C_{18}	c_2 d_2
T_6	a_4 b_4 c_3 d_3

	S'_c
T_1	a_1 b_1 c_1 d_1
C_{19}	c_2 d_2
T_6	a_4 b_4 c_3 d_3

Fig. 13. *Left* - Current summary, S_c after third iteration (Size = 3, Information Loss = 10). *Right* - The optimal summary S'_c (Size = 3, Information Loss = 8).

select_best - Method 3
Input: T: a transaction data set.
S_c: current summary.
C_c: candidate set.
k_s: scoring parameter.
δ: increment parameter for k_s.
Output : C_{best}: best candidate.
Method:

```
1.   for each C_i in C_c
2.       score(C_i, S_c) = k_s*gain(C_i, S_c) - loss(C_i, S_c)
3.   end for
4.   max-score = maximum(score(C_i, S_c), ∀C_i ∈ C_c)
5.   for each C_i in C_c
6.       if((score(C_i, S_c) == max-score) & (gain(C_i, S_c) > 1))
7.           return C_best = C_i
8.       end if
9.   end for
10.  k_s = k_s + δ
11.  Goto 1
12.  End
```

Fig. 14. *select_best* - Method 3

6.3. Method 3

The third method to determine the best candidate makes use of a parameter k_s, which combines the two quantities $gain(C_i, S_c)$ and $loss(C_i, S_c)$ to obtain a single value, denoted by $score(C_i, S_c)$. The method is shown in Figure 14. The first step calculates the score for each candidate using k_s. The candidate with highest score is chosen as the *best* candidate. Initially k_s is chosen to be 0. This favors the candidates with very small information loss. If all candidates with the highest score have $size(C_i, S_c) <= 1$, then k_s is incremented by a small value, δ. This allows larger candidates to have higher score by offsetting the larger information loss associated with them, and thus be considered for selection into the summary.

The value of k_s can be initialized to a value greater than 0, which would result in selection of larger candidates initially. Using this method again does not guarantee an optimal solution and depends on the initial value of k_s and δ.

6.4. Method 4

Each of the above three methods require the rescoring of $gain(C_i, S_c)$ and $loss(C_i, S_c)$ for each candidate after each iteration. The method 4, shown in Figure 15 does not require these computations but makes use of the quantity $feature\_loss(C_i)$ which refers to the weighted sum of the features missing in a candidate. Note that this quantity does not change over the iterations and hence is computed only once. The method to determine the best candidate uses parameter ϵ, which defines a upper threshold on $feature\_loss(C_i)$. Only those candidates which have $feature\_loss(C_i)$ less than or equal to this threshold are considered for selection. Out of these the candidate with largest value of $gain(C_i, S_c)$ (>1) is selected as

select_best - Method 4
Input: T: a transaction data set.
S_c: current summary.
C_c: candidate set.
ϵ: loss level.
δ: increment parameter for ϵ.
Output : C_{best}: best candidate.
Method:
for each C_i in C_c
$C' = \{C_i \mid C_i \in C_c \; \& \; gain(C_i, S_c) > 1) \; \& \; feature\_loss(C_i) <= \epsilon)\}$
end for
if($C'_c == \{\}$)
$\epsilon = \epsilon + \delta$
Goto 1
end if
$best = argmax_{C_i \in C'}(gain(C_i, S_c))$
return C_{best}
End

Fig. 15. *select_best* - Method 4

the best candidate. Initially ϵ is chosen as 0. Thus only candidates with 0 features missing are considered. If all candidates which fall under ϵ threshold have $gain(C_i, S_c) \leq 1$, then ϵ is incremented by a small value, δ. This allows larger candidates to be considered for selection into the summary.

6.5. Discussion

All the four methods discussed above select a candidate which they consider is the best with respect to a heuristic. We presented examples for first two methods where this choice might not always lead to a *globally optimal solution*. The last two methods make use of a user defined parameter and a wrong choice of this parameter can lead to suboptimal solutions. We have investigated each of these approaches and evaluated them on different network data sets (described in next section) and observed that all of them perform comparably in terms of the ICC curve characteristics with respect to each other.

7. Experimental Evaluation And Results

In this section we present the performance of our proposed algorithms on network data. We compare the performance of BUS with the clustering based approach to show that it performs better in terms of achieving lower information loss for a given degree of compaction. As we had mentioned earlier, the clustering based algorithm captures the clusters in the data and summarizes the transactions belonging to those clusters well. But the presence of infrequent patterns can ruin the cluster descriptions and result in high information loss. The experimental results presented in this section highlight this fact by choosing different data sets which have different characteristics in terms of the natural clustering in the data. We also illustrate the summaries obtained for different algorithms to

Data Set	Size	Source	Characteristics
AD1	1000	Artificially Generated	Contains 5 clusters with 200 identical transactions in each cluster
AD2	1100	Artificially Generated	For each cluster in AD1 20 transactions different in exactly one feature are added
SKAION	8459	SKAION Data set, Scenario S29	Contains normal traffic belonging to natural clusters mixed with outlying attack traffic
DARPA	2903	DARPA Data set, 6 different attack related traffic from training week 4, day 5 data	Most of the transactions belonged to clusters corresponding to each of the larger attacks while some were outliers

Table 8. Description of the different datasets used for experiments.

make a qualitative comparison between them. The algorithms were implemented in GNU-C++ and were run on the Linux platform on a 4-processor *intel*-i686 machine.

7.1. Input Data

We ran our experiments on four different artificial datasets as listed in Table 8. The first two data sets, $AD1$ and $AD2$ were artificially generated such that they contained 5 clusters such that each cluster contained the same transaction replicated 200 times. $AD1$ contained only these pure clusters. $AD2$ contained outliers injected with respect to each of the cluster. The SKAION and DARPA data sets were generated by DARPA [15] and SKAION corporation [1] respectively, for the evaluation of intrusion detection systems. The DARPA dataset is publicly available and has been used extensively in the data mining community as it was used in KDD Cup 1999. The SKAION data was developed as a part of the ARDA funded program on information assurance and is available only to the investigators involved in the program. Both these datasets have a mixture of normal and attack traffic. The DARPA data set was a subset of the week 4, Friday, training data containing only attack related traffic corresponding to the following attacks - *warezclient, rootkit, ffb, ipsweep, loadmodule* and *multihop.*

All of these datasets exhibit different characteristics in terms of data distribution. We measure the distribution of the data using the *lof* (local outlier factor) score (see [6]). The distribution for *lof* scores for $AD1$ data set is shown in Figure 16(a). Since all transactions belong to one of the 5 clusters, all transactions have a lof score of 1. Similar plot for data set $AD2$ in Figure 17(a) shows that some of the transactions have a higher *lof* score since they are outliers with respect to the clusters. Figure 18(a) gives the distribution of the *lof* (local outlier factor) score (see [6]) for the transactions in the SKAION dataset. The *lof* score reflects the outlierness of a transaction with respect to its nearest neighbors. The transactions which belong to tight clusters tend to have low *lof* scores while outliers have high *lof* scores. For the SKAION dataset we observe that there are a lot of transactions which have high outlier scores. The *lof* distribution for the DARPA dataset in Figure 18(e) shows that most of the transactions belong to tight clusters, and only a few transactions are outliers.

feature name	weight
Source IP	3.5
Source Port	0
Destination IP	3.5
Destination Port	2
Protocol	0.1
Time to Live(ttl)	0.1
TCP Flags	0.1
Number of Packets	0.3
Number of Bytes	0.3
Window Size	0.1

Table 9. Different features and their weights used for experiments.

7.2. Comparison of ICC curves for the clustering-based algorithm and BUS

We ran the clustering based algorithm by first generating clusters of different sizes using the *CLUTO* hierarchical clustering package [14]. For finding the similarity between transactions, the features were weighted as per the scheme used for evaluating the information loss incurred by a summary. We then summarized the clusters as explained in Section 3. For BUS, we present the results using frequent itemsets generated by the *apriori* algorithm with a support threshold of 2 as the candidates. The BUS algorithm was executed using *method 1* (see Section 6.1)[4]. The different features in the data and the weights used are given in Table 9. These weights reflect the typical relative importance given to the different features by network analysts. The continuous attributes in the data were discretized using *equal depth binning* technique with a fixed number of intervals (= 75) and then used as categorical attributes. Figures 16(b) and 17(b) show the ICC curves for the clustering-based algorithm and BUS on data sets $AD1$ and $AD2$ respectively. Since $AD1$ contains 5 pure clusters, both schemes show no information loss till the compaction gain is 200 (summary size = 5). For compaction more than 200, the information loss increases sharply, since the 5 clusters were chosen to be distinct from each other. Hence no larger summary could be found which could merge any two clusters efficiently. In the second data set $AD2$, there are 100 outlying transactions. The figure shows that the performance of the clustering based approach degrades rapidly as the compaction gain is increased. This happens because some of the outlying transactions are forced to belong to the natural clusters, which makes the cluster description very lossy, and hence incurs a large information loss for all members of that cluster.

Figures 18(b) and 18(f) show the ICC curves for the clustering-based algorithm and BUS on the DARPA and SKAION data sets respectively. From the two graphs we can see that BUS performs better than the clustering-based approach. We also observe that the difference in the curves for each case reflects the *lof* score distribution for each dataset. In the SKAION dataset there are a lot of outliers which are represented poorly by the clustering-based approach while BUS handles them better. Hence the difference in the information loss is very high. In the DARPA dataset, most of the transactions belong to well-defined clusters which are represented equally well by both the algorithms. Thus, the

[4] The results from running BUS with other methods were also comparable with this method and hence are not presented here.

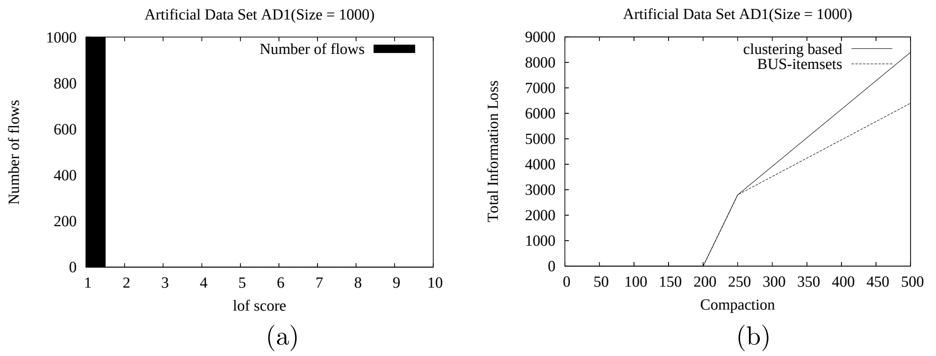

Fig. 16. (a). Distribution of *lof* scores for the $AD1$ data set. (b). ICC curves using the clustering based algorithm and BUS(method 1) on artificial dataset $AD1$

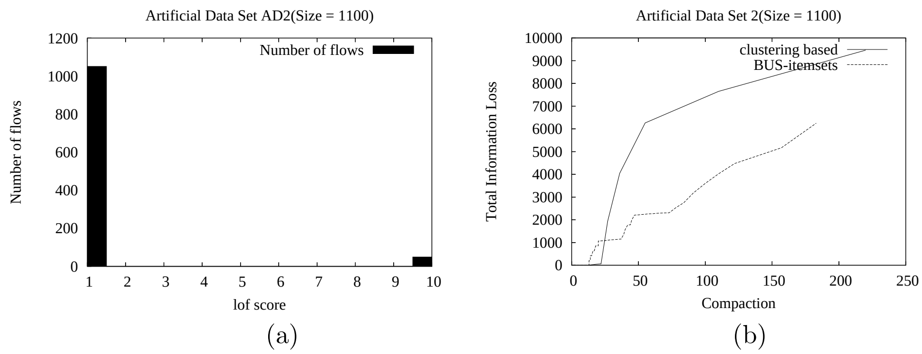

Fig. 17. (a). Distribution of *lof* scores for the $AD2$ data set. (b). ICC curves using the clustering based algorithm and BUS(method 1) on artificial dataset AD2

difference in information loss for the two algorithms is not very high in this case.

To further strengthen our argument that clustering tends to ignore the infrequent patterns and outliers in the data, we plot the information loss for transactions which have lost a lot of information in the summary. Figure 18(c) shows the difference in the ICC curves for the transactions in the DARPA dataset which have lost more than 70% information. The graph shows that for BUS, none of the transactions lose more than 70% information till a compaction gain of about 220, while for the clustering based approach, there are considerable number of transactions which are very poorly represented even for a compaction gain of 50. A similar result for the SKAION dataset in Figure 18(g) shows that BUS generates summaries in which very few transactions have a high loss, which is not true in the case of the clustering based approach.

Figure 18(d) shows the difference in the ICC curves for each algorithm for the transactions which have lost less than 70% of information for the DARPA dataset. This plot illustrates the difference in behavior of the two algorithms in terms of summarizing the transactions which belong to some frequent pattern in the data. The clustering based approach represents these transactions better

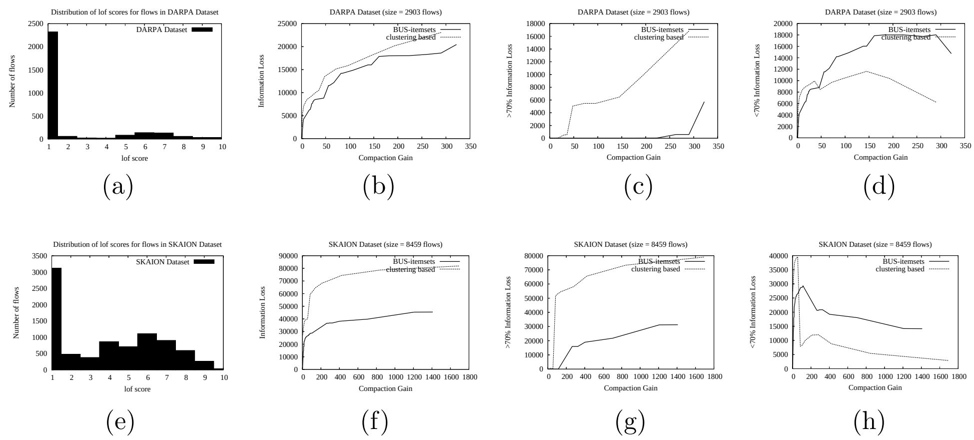

Fig. 18. Figures (a) – (d) present results for the DARPA dataset, Figures (e) – (h) present results for SKAION dataset. (a,e) Distribution of *lof* scores. (b,f) ICC Curve for the clustering based algorithms and BUS. (c,g) Sum of the Information Loss for transactions that have lost more than 70% of information. (d,h) Sum of the Information Loss for transactions that have lost less than 70% information.

than BUS. A similar result can be seen for the SKAION dataset in Figure 18(h).

7.3. Qualitative Analysis of Summaries

In this section we illustrate the summaries obtained by running the clustering based algorithm (see Table 10), and BUS using frequent itemsets (see Table 11) on the DARPA dataset described above. This dataset is comprised of different attacks launched on the internal network by several external machines. The tables do not contain all the features due to the lack of space. However, the information loss was computed using all the features shown in Table 9.

In the summary obtained from the clustering based approach, we observe that S_1 and S_3 correspond to the *icmp* and *udp* traffic in the data. Summaries S_2, S_4 and S_6 represent the *ftp* traffic on port 20, corresponding to the *warezclient, loadmodule* and *ffb* attacks which involve illegal *ftp* transfers. S_5 represents traffic on port 23 which correspond to the *rootkit* and *multihop* attacks. The rest of the summaries, S_7-S_{10}, do not have enough information as most of the features are missing. These cover most of the infrequent patterns and the outliers which were ignored by the clustering algorithm. Thus we see that the clustering based algorithm manages to bring out only the frequent patterns in the data. The summary obtained from BUS gives a much better representation of the data. Almost all the summaries in this case contain one of the IPs (which have high weights), which is not true for the output of the clustering-based algorithm. Summaries S_1 and S_2 represent the *ffb* and *loadmodule* attacks since they are launched by the same source IP. The *warezclient* attack on port 21 is represented by S_3. The *ipsweep* attack, which is essentially a single external machine scanning a lot of internal machines on different ports, is summarized in S_6. S_5 summarizes the connections which correspond to internal machines which replied to this scanner. The real advantage of this scheme can be seen if we observe summary S_9

	size	src IP	sPort	dst IP	dPort	proto	packets	bytes
S_1	513	***	0	***	0	icmp	[1,1]	[28,28]
S_2	51	172.16.112.50	20	***	***	tcp	***	***
S_3	119	***	***	***	***	udp	***	***
S_4	362	197.218.177.69	20	***	***	tcp	[5,5]	***
S_5	141	***	***	***	23	tcp	***	***
S_6	603	172.16.114.148	20	***	***	tcp	***	***
S_7	507	***	***	***	***	tcp	***	***
S_8	176	***	***	***	***	tcp	***	***
S_9	249	***	***	***	***	tcp	***	***
S_{10}	182	***	***	***	***	tcp	***	***

Table 10. A size 10 summary obtained for DARPA dataset using the clustering based algorithm. Information Loss=23070.5

	size	src IP	sPort	dst IP	dPort	proto	packets	bytes
S_1	279	***	***	135.13.216.191	***	***	***	***
S_2	364	135.13.216.191	***	***	***	***	***	***
S_3	138	***	***	***	21	tcp	***	***
S_4	76	172.16.112.50	***	***	***	***	***	***
S_5	249	***	***	197.218.177.69	***	***	***	***
S_6	1333	197.218.177.69	***	***	***	***	***	***
S_7	629	172.16.114.148	***	***	***	tcp	***	***
S_8	153	***	***	***	23	tcp	***	***
S_9	1	172.16.114.50	23	207.230.54.203	1028	tcp	[1,1]	[41,88]
S_{10}	5	***	0	197.218.177.69	0	icmp	[1,1]	[28,28]

Table 11. A size 10 summary obtained for DARPA dataset using BUS algorithm. Information Loss=18601.7

which is essentially a single transaction. In the data, this is the only connection between these two machines and corresponds to the *rootkit* attack. The BUS algorithm preserves this outlier even for such a small summary because there is no other pattern which covers it without losing too much information. Similarly, S_{10} represents 5 transactions which are *icmp* replies to an external scanner by 5 internal machines. Note that these replies were not merged with the summary S_5 but were represented as such. Thus, we see that summaries generated by BUS algorithm represent the frequent as well as infrequent patterns in the data.

8. Related Work

Compression techniques such as *zip, mp3, mpeg etc.* also aim at reduction in data size. But compression techniques are motivated by system constraints such as processor speed, bandwidth and disk space. Compression schemes try to reduce the size of the data for efficient storage, processing or data transfer. Summarization, on the other hand, aims at providing an overview of the data, thereby allowing an analyst to get an idea about the data without actually having to analyze the entire data.

Many researchers have addressed the issue of finding a compact representation of frequent itemsets [2, 20, 11, 19, 7, 5]. However, their final objective is to approximate a collection of frequent itemsets with a smaller subset, which is different from the problem addressed in this paper, in which we try to represent a collection of transactions with a smaller summary.

Text summarization [18] is a widely-researched topic in the research community, and has been addressed mostly as a natural language processing problem which involves semantic knowledge and is different from the problem of summarization of transaction data addressed in this paper. Another form of summarization is addressed in [12] and [16], where the authors aim at organizing and summarizing individual rules for better visualization while not addressing the issue of summarizing the data.

The closest related work on summarization of categorical data sets is by Wang and Karypis [24]. This paper proposes an algorithm (SUMMARY) to find a set of frequent itemsets (based on a support threshold), which is called a *summary-set*, for a given set of transactions. The *summary-set* is found by determining the longest frequent itemset which covers a transaction, for each transaction and then taking union of all such longest frequent itemsets. The *summary-set* is then used to determine clusters for the given data set by treating each member of the *summary-set* as a cluster such that all transactions which considered that member as their longest representation belong to the same cluster. The authors claim that the *summary-set* determined using the SUMMARY algorithm is a good summary of the entire data set. Indeed this method can be viewed as one instance of the top-down approach for computing summaries. However there are several shortcomings associated with it as discussed below

– The *summary-set* does not guarantee to cover every transaction belonging to the data set. Outlying transactions which do not match with any other transaction on any feature will not exist in any frequent itemset (even if the support threshold is 2 transactions). Such transactions will not have any representative in the *summary-set* and will be completely lost. This would be highly undesirable in applications where outliers are of great significance to analysts. As mentioned in the introduction, every transaction has to have some form of representation in the final summary. We must note that the real objective of the *summary-set* algorithm (as stated in the paper) is to find clusters.
– This method does not try to explicitly trade-off compaction gain for information loss. The compaction gain is very indirectly controlled by the support threshold parameter. Thus to reduce the size of *summary-set*, the support threshold can be increased. But this would result in more and more infrequent transactions getting completely lost.

9. Concluding Remarks and Future Work

The two schemes presented for summarizing transaction datasets with categorical attributes demonstrated their effectiveness in the context of network traffic analysis. A variant of our proposed two-step approach is used routinely at the University of Minnesota as a part of the MINDS system to summarize several thousand anomalous netflows into just a few dozen summaries. This enables the analyst to visualize the suspicious traffic in a concise manner and often leads to the identification of attacks and other undesirable behavior that cannot be captured using widely used intrusion detection tools such as SNORT.

The summarization techniques presented in this paper assume that all transactions in the data set are equally important. In several applications, the transactions might have different levels of importance. In such cases it will be desirable for higher ranked transactions to incur low information loss while lower ranked transactions can tolerate a little higher information loss.

A typical example can be found in network anomaly detection domain where the network flows are ranked based on their anomaly scores. The main challenge that arises in adapting our proposed summarization techniques to this problem is how to incorporate the knowledge of ranks while scoring the candidates to achieve the above stated objective. We are currently investigating a few possible approaches in this direction.

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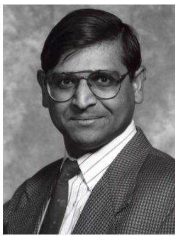
Author Biographies



Vipin Kumar is currently William Norris Professor and Head of the Computer Science and Engineering Department at the University of Minnesota. His research interests include high-performance computing and data mining. He has authored over 200 research articles, and has coedited or coauthored 9 books including the widely used text books *Introduction to Parallel Computing* and *Introduction to Data Mining*, both published by Addison Wesley. He has served as chair/co-chair for many conferences/workshops in the area of data mining and parallel computing, including the IEEE International Conference on Data Mining (2002) and the 15th International Parallel and Distributed Processing Symposium (2001). He serves as the chair of the steering committee of the SIAM International Conference on Data Mining, and is a member of the steering committee of the IEEE International Conference on Data Mining. Dr. Kumar serves or has served on the editorial boards of several journals including *Knowledge and Information Systems*, *Journal of Parallel and Distributed Computing* and *IEEE Transactions of Data and Knowledge Engineering* (1993–1997). He is a Fellow of the ACM and IEEE, and a member of SIAM.

Varun Chandola received his BTech degree in Computer Science from the Indian Institute of Technology, Madras, India in 2002. He is currently a PhD student in the Computer Science and Engineering Department at the University of Minnesota. His research interests include data mining, cyber-security and machine learning.

Correspondence and offprint requests to: Varun Chandola, Department of Computer Science, University of Minnesota, Minneapolis, MN 55414, USA. Email: chandola@cs.umn.edu