Solving a Hard Instance of Suspicious Behaviour Detection with Sparse Binary Vectors Clustering

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Keywords: Machine Learning, Clustering, Sparse Binary Vector, Malicious Behaviour, Infrastructure Security.

Abstract: In this article we present a study dealing with the problem of detecting a very small subset of suspicious and malicious behaviours represented by sparse binary vectors in a population of individuals significantly larger. The main problem lies in the fact that malicious behaviours, in the case of sparse vectors, are difficult to distinguish from normal behaviours. Despite the fact that vectors are apparently strongly unbalanced, this property cannot be exploited since the objects to classify (behaviours) do not exhibit strongly enough frequencies discrepancy. It is not possible to work on detection directly and it is therefore necessary to go through a preliminary phase of vector partitioning (representing normal or malicious behaviour) to select a reduced subset concentrating with a high probability most of the vectors corresponding to malicious behaviours. We have been working on a set of anonymized real data from terrorism-related cases.

1 INTRODUCTION

An essential goal in security relates to the ability of distinguishing malicious objects (attackers, malware, events...) from normal (benign) objects (users, legitimate programs, normal events...). Since a few year machine-learning and data analysis provide interesting and often powerful tools to achieve this goal in the field of (cyber)security. Once the objects have been carefully modelled by the right objects, a lot of algorithms nowadays are available to solve this question efficiently and accurately. Among many other, modelling object by means of Boolean vectors has proved to be very powerful. In this case, we consider attributes (features) seen as categorical variables and the corresponding bit value describes the presence or the absence of the relevant attribute. Then simple similarity measures enables either the identification of homogeneous subsets of objects (supervised techniques like clustering) or to identify a given unknown object as being closer to one particular family of known objects than to any other.

However malicious objects adapt and strive to evade the known detection techniques. Optimally either they mimic as much as possible normal objects or they limit the leak of information that could be useful for their detection. They can also force the analyst to face complexity issue that makes the detection far more difficult.

In this paper, we are going to address an unusual problem where all classical approaches (Aggarwal, 2015, Chap. 6 & 7) are not working. This means that they do not provide better results than would a random approach. When considering the specific case of unbalanced binary data clustering (*i.e* data exhibit disparities in observed frequencies) (He and Garcia, 2009) we did not obtain better or more satisfying results. Despite the fact that ou data appear strongly unbalanced (we consider 16-bit binary vectors having constant Hamming weight of 5 then $P[\text{attibute}_i = 1] = \frac{5}{16}$), the unbalancedness property here is not relevant in our specific cases study. We came to the conclusion that the difficulty relates more to the vector sparsity than to the vector attributes unbalancedness. Behaviours (vectors) are described as a collection of basic actions/properties that are realized or not (attributes). Due to operational constraints (Section 3), only a reduced number of attributes can be collected at a time (sparsity). Moreover the number of behaviours recorded are close enough to the maximal number of possible behaviours. Our problem consists then in clustering behaviours that do not exhibit exploitable frequencies discrepancies, at least by known unbalanced binary data clustering techniques.

The problem comes from the analysis/detection of terrorist behaviours in a population. A French governmental security entity has provided us with a database

Filiol, E. and Hota, A.
Solving a Hard Instance of Suspicious Behaviour Detection with Sparse Binary Vectors Clustering.
DOI: 10.5220/0007347206350644
In *Proceedings of the 5th International Conference on Information Systems Security and Privacy (ICISSP 2019)*, pages 635-644
ISBN: 978-989-758-359-9

of binary vectors that describe behaviour patterns for a number of individuals. Due to the sensitivity of the data, we got only an anonymized version of the actually collected vectors.

The main interest of this study was to be aware that in a few cases we cannot find an optimal, ideal solution (it does not clearly exist). However, the operational view can orientate new approaches that are suitable and admissible for the people working on the field. In our case, the aim was no longer to extract a subset of "positive" vectors (potentially suspicious behaviours) as usual approaches strive to but to partition the dataset in a suitable enough way to make detection then possible by a subsequent, intelligence-driven step. It is worth mentioning that only this latter step is able to confirm which vector relates to a suspicious actor or not as soon as the analyst can work on a significantly reduced subset. So we have to switch from a classical clustering problem to a dataset refining problem.

The paper is organized of follows. After presenting the state-of-the-Art in binary vector clustering applied to the security domain, Section 3 formalises the problem by considering sparse binary vectors. Then Section 4 explains how which techniques we have combined to extract a reduced subset from the initial set without loosing to much information about the malicious behaviours. Section 5 presents the results which have been obtained on a set of real data and on sets simulating this set. Finally we conclude in Section 6.

2 STATE-OF-THE-ART IN SECURITY

Clustering techniques find a wide variety of applications in information security including anomaly detection, vulnerability characterization, etc. We propose to summarize the state-of-the-art regarding categorical data (binary) clustering when applied to the security field.

2.1 Clustering Binary Vectors

Münz, Li and Carle (Münz et al., 2007) describe the use of clustering for anomaly detection in network traffic. They present a flow-based anomaly detection scheme using *k*-means clustering. The initial training data consists of unlabelled network flow records containing both normal and anomalous traffic. These records are transformed into feature datasets which are then clustered into normal and anomalous traffic. The centroids of these clusters are then used in distance-based anomaly detection in new network flow data.

Nalavade and Meshram (Nalavade and B. Meshram, 2014) investigate clustering approaches for network intrusion detection. Intrusion detection systems using data mining approaches enable us to search patterns and rules in large amount of audit data. Classification-based data mining models for intrusion detection have often proven ineffective due to dynamic patterns in network data. They experiment with *k*-means clustering algorithm on the KDD dataset and measure the performance based on detection rates and false positive rate with different cluster values.

Syarif, Prugel-Bennett and Wills (Syarif et al., 2012) describe the advantages of using the anomaly detection approach over the misuse detection technique in detecting unknown network intrusions or attacks. They investigate five different clustering algorithms: *k*-Means, improved *k*-Means, *k*-Medoids, EM clustering and distance-based outlier detection algorithms. They show that misuse detection techniques, which implemented four different classifiers (naïve Bayes, rule induction, decision tree and nearest neighbour) failed to detect network traffic, which contained a large number of unknown intrusions. Anomaly detection,on the other hand, showed better results, especially with distance-based outlier detection algorithms.

Wazid (Wazid, 2014) investigates the feasibility of using clustering techniques for security in wireless sensor networks. He proposes a hybrid anomaly detection technique based on k-means clustering. He shows the effectiveness in detecting misdirection and blackhole attacks.

Riadi et.al.(Riadi et al., 2013) describe the use of clustering techniques to characterize types of attacks for forensics. Network data, including packets relevant to the attacks being investigated are stored in a log file. This data is grouped using *k*-means clustering technique into three categories and mapped based on source and target. They thus propose a framework for forensic investigations.

Li, Venter and Eloff (Li et al., 2004) describe a way to categorize vulnerabilities in the CVE database and present a method to cluster the vulnerabilities using self-organizing feature maps.

K-anonymization techniques have become important in many data privacy solutions. A key requirement is to ensure data anonymization while avoiding information loss. Byun et.al.(Byun et al., 2006) propose an approach using clustering techniques. They formulate a *k*-member clustering problem, prove that the problem is NP-hard and present a greedy algo-

rithm with a complexity of $O(n^2)$. They also propose extension to reduce classification errors.

Pai (Pai, 2015) (and its references) applies clustering techniques to the malware detection problem with the goal of classifying malware as part of a fully automated detection system. Clusters are computed using K-means and EM clustering algorithms, with scores obtained from Hidden Markov Models.

2.2 Unbalanced Binary Data Clustering

As explained in the introduction, solving our problem deals more with vectors sparsity that with the fact that underlying attributes exhibits strong frequencies discrepancy. A lot of papers have been published regarding machine learning techniques of unbalanced data. The interested reader may refer to (He and Garcia, 2009; Krawczyk, 2016) (and their respective bibliography).

2.3 Clustering Sparse Binary Vectors

A number of approaches have been applied to the specific problem of clustering sparse binary vectors. Distance-based approaches have been quite popular along with other techniques like EM based approaches, subspace clustering, spectral clustering, etc.

Choi, Cha and Tappert (Choi et al., 2010) survey binary similarity and distance measures. The effectiveness of many clustering techniques often comes down to selecting the right distance metric and as such this study stays relevant regardless of techniques used. They study 76 measures and show correlations through hierarchical clustering.

Jian et.al (Jian et al., 2018) study similarity analysis of categorical data that is not independent and identically distributed (non-IID) and propose a Coupled Metric Similarity (CMS) for unsupervised learning which flexibly captures the value-to-attribute-to-object heterogeneous coupling relationships. The similarities are learnt in terms of intrinsic heterogeneous intra- and inter-attribute couplings and attribute-to-object couplings in categorical data and CMS are shown to flexibly adapt to IID to non-IID data. They further incorporate CMS into spectral clustering and k-modes clustering.

Conventional clustering techniques have often proven ineffective when dealing with high-dimensional spaces because of the inherent sparsity of the data points. Gan and Wu (Gan and Wu, 2004) propose an iterative algorithm called SUBCAD for clustering high dimensional categorical data sets, based on the minimization of an objective function for clustering. They further propose an objective function that determines the subspace associated with each cluster. They go on to prove various properties of this objective function and propose a fast algorithm to find the subspace associated with each cluster.

Su and Su (Su and Su, 2017) study the clustering problem for categorical data and propose a method to find distinctive features in categorical datasets. Their model works by comparing pooled within-cluster mean relative difference and then partitioning the data upon such features and deriving the subspace of the subgroups.

Mahdi, Abdelrahman and Bahgat (Mahdi et al., 2018) propose a new similarity measure for categorical datasets. The Probability of the Weights of Overlapped items (PWO) estimates the goodness of clusters. The goal is to maximize frequent items within clusters and minimize items overlapping between clusters. An F-Tree clustering model is used to compare the effectiveness of PWO with other measures.

Ordonez (Ordonez, 2003) proposes three variants of the K-means algorithm to cluster binary data streams including On-line k-means, Scalable k-means, and Incremental k-means. Incremental k-means is presented as a scalable solution that finds higher quality clusters in less time. A mean-based initialization and incremental learning are used to obtain higher quality clusters.

3 FORMALISATION OF THE PROBLEM

In this section we are going to formalize the problem we have to address when considering the very specific operational constraints of the underlying environment. Contrary to usual set clustering problem (see Section 2) where objects to be classified are rather easy to partition, in our case the usual techniques do not work efficiently enough to do better than a random partitioning.

Our dataset $\mathcal{A}$ is made of binary vectors of size 16. Thus $\mathcal{A} = \{v_0, v_1, \ldots, v_N\}$. Each of these vectors v_i is representing either a likely malicious behaviour or a normal behaviour in the following way, considering a set of attributes of interest $\mathcal{B} = \{b_0, b_1, \ldots, b_{15}\}$. For confidentiality purposes, we do not know what each attribute b_i is representing. Only an arbitrary labelling has to be considered. Each Boolean value for attribute b_i is modelling a "basic" behaviour in a "complex" behaviour v_j. Thus to summarize:

$$\forall j \in \{0,1,\ldots,N\} \qquad v_j = (v_j^0, v_j^1, \ldots, v_j^{15})$$

$$v_j^i = \begin{cases} 1 & \text{if basic behaviour } b_i \text{ is observed} \\ 0 & \text{otherwise} \end{cases}$$

Due to operational (technical, legal) constraints of the surveillance and intelligence system, only 16 different attributes can be considered and only 5 attributes can be collected for a given individual j at a time (for one set only, denoted $\mathcal{D}_1$, however 6 attributes have been collected). So the Hamming weight of the corresponding vector $H[v_j] = 5$ (or $H[v_j] = 6$ for set $\mathcal{D}_1$). From a pure combinatorial point of view there are only 4,368 such vectors (resp. 8,008 for set $\mathcal{D}_1$). Feedbacks from the field shows that the number of actually collected vector may be very close from this theoretical upper bound, unless a manual, intelligence driven preprocessing step is performed. Moreover, the same behaviour pattern can be recorded many times both for suspicious and non suspicious individuals. As a consequence discriminating malicious behaviours from non malicious ones become a hard task for two main reasons:

- each vector is containing a limited amount of information due to its sparsity and due to the limited number of attributes that are considered,
- each of the basic behaviours b_i is not malicious in itself since it may equally be realised ($v_j^i = 1$) or not ($v_j^i = 0$). It implies that discriminating malicious complex behaviours from non malicious ones cannot be performed directly. In fact the actual malicious state must be related to the environment in which individuals evolve and operate.

As far as the last point is concerned, it is then impossible to work on the full initial dataset to identify the individuals that potentially behave in a suspicious way. Indeed each vector has to be interpreted in connection with the collecting environment. However, this final step becomes "easy" (by a subsequent step) as soon as the dataset has a reduced size. So here the aim is no longer to cluster data with the hope to get one cluster containing all the malicious instances (plus a limited number of non malicious ones). Instead we wish to obtain a partition $\mathcal{P} = \{\mathcal{A}_1, \mathcal{A}_2, \ldots, \mathcal{A}_k\}$ of the set $\mathcal{A}$ such that at least one of the cluster contains at least half of the malicious instances (that will be identified as such in the subsequent, intelligence-driven step).

Let us denote $\mathcal{A}_i^1$ the cluster which contains most of the target vectors (malicious behaviours). The key parameters are k, the number of final clusters, $|\mathcal{A}_i|$ the size of the different subset of $\mathcal{P}$ and $|\mathcal{A}_i^1|$, the size of the target cluster. It is considered that is $k \geq 4$ and $|\mathcal{A}_i^1| \approx \frac{|\mathcal{A}|}{k}$ while in average $|\mathcal{A}_j| \approx \frac{|\mathcal{A}|}{k}$ for $j \neq i$, then the results are operationally admissible and viable.

4 REDUCED SUBSET EXTRACTION PROBLEM

Firstly we consider three approaches to cluster our datasets: the leading eigenvector method, the correlation explanation techniques and the classical k-Means technique applied on sentence vectors. Then we develop a combined clustering step using a majority voting scheme with these three approaches.

4.1 The Leading Eigenvector Method

The leading eigenvector method (Newman, 2006) has proved to be quite effective in community detection. It uses the eigenvectors of matrices to detect community structure in large networks.

The data is preprocessed prior to the actual clustering. This step is relatively simple since there are no missing values. Also, since these are binary vectors, scaling is not needed. At this stage we run some precomputations to figure out thresholds to be used while creating graphs using the datasets. These thresholds are based on two comparisons:

1. The number of equal corresponding elements between any two feature vectors. The workflow using this comparison will be referred to npsum_{01} in this document. If we consider vectors v_i and v_j then it consists in considering the Hamming weight of $\overline{v_i \& v_j}$ where $\overline{v}$ denotes the bitwise negation of vector v and & denotes the bitwise AND.
2. The number of corresponding elements of any two feature vectors both being equal to 1. In this case, if the corresponding elements are both 0, they are simply ignored. The workflow using this comparison will be referred to npsum_1 in this document. It is equivalent of the dot product of the two vectors.

The following example describes how the threshold values were computed. Let us consider three vectors from the dataset $\mathcal{D}_1$ (length 16, weight 6):

- $v_0 = (0,1,1,0,1,0,1,0,0,1,0,1,0,0,0,0)$
- $v_1 = (0,0,1,0,1,0,1,1,0,1,0,1,0,0,0,0)$
- $v_2 = (0,1,1,0,0,0,1,1,0,1,0,0,0,1,0,0)$

Then weights W_{ij} are computed for possible edges between all vector pairs i and j and we have:

- For npsum_{01}, $W_{01} = 14 - W_{02} = 12 - W_{12} = 12$
- For npsum_1, $W_{01} = 5 - W_{02} = 4 - W_{12} = 4$

The clustering is then done in two stages each consisting of a 50 % split of the dataset being considered. Each stage consists of the following steps (terms and techniques are those used in (Newman, 2006)):

1. Build the undirected graph using predetermined threshold values. For that purpose we use *Networkx* (Aric Hagberg, 2018) in Python.
2. Compute the adjacency matrix for this graph.
3. Compute the modularity matrix.
4. Compute the eigenvalues and corresponding eigenvectors for the modularity matrix.
5. Assign clusters based on signs of the elements of the eigenvector corresponding to the most positive eigenvalue.

The process was applied with npsum_1 and npsum_{01} as described previously. For three of the resulting datasets there was no difference in the results. For the fourth one npsum_{01} gave slightly better results in terms of preserving the original positives in the final clustering. The threshold value remains consistent across the two stages.

Two graphs were built for each dataset, one with a threshold value equal to 12 and the other with a threshold value equal to 14. For each pair of feature vectors, if the npsum value exceeds the threshold, an edge is created between the nodes representing the two feature vectors. This allows us to minimize the number of edges without losing any useful information.

An adjacency matrix is a square matrix used to represent a finite simple graph. The elements of the matrix indicate whether pairs of vertices are adjacent or not in the graph. For the purposes of this analysis, only unweighed adjacency matrices are considered. The following function takes a *NetworkX* graph and computes the adjacency matrix, returning it as a *scipy* (Jones et al., 01) sparse matrix.

Modularity is a measure of the structure of a network. A network with high modularity has dense connections between nodes within communities while sparse connections between nodes in different communities.

For any two nodes i and j corresponding to binary vectors v_i and v_j respectively,

- k_i and k_j denote the expected degree of each node
- P_{ij} denotes the number of expected edges between node i and node j.

We begin with the constraint that the expected degree is equal to the actual degree of the node taken from the adjacency matrix. Thus summing the columns of the adjacency matrix gives us the expected degree for each node in the graph.

Let m denote the total number of edges in the graph. Then P_{ij} is given by

$$P_{ij} = \frac{k_i \times k_j}{m}$$

Given an adjacency matrix A, we can now compute the corresponding modularity matrix B such that

$$B_{ij} = A_{ij} - P_{ij}$$

At this stage the eigenvalues and corresponding eigenvectors are computed for the modularity matrix B. Cluster assignment is now done based on the sign of the elements of the eigenvector corresponding to the most positive eigenvalue.

4.2 The Correlation Explanation Method

Correlation Explanation aims at learning a hierarchy of abstract representations of complex data by optimizing an information-theoretic objective (Steeg and Galstyan, 2014; Ver Steeg and Galstyan, 2014). Let X denote a discrete random variable while $P(X)$ denotes a probability distribution over X and $|X|$ denotes the cardinality of the set of values that X may take and is always finite. Assuming n random variables, $G \subseteq \mathbb{N}_n = \{1,2,\ldots,n\}$ and X_G is the corresponding subset of random variables. Let us denote $H(X)$ the entropy of X and $I(X_1 : X_2)$ as the mutual information between the two random variables X_1 and X_2 (Cover and Thomas, 2006).

The measure of mutual information used in this method is known as total correlation (Watanabe, 1960), multi-information (Studený and Vejnarová, 1998) or multivariate mutual information (Kraskov et al., 2005). It is defined as

$$TC(X_G) = \sum_{i \in G} (H(X_i) - H(X_G)$$

The extent to which another variable Y explains the correlations in X can be measured by how much the total correlation is reduced (Steeg and Galstyan, 2014).

$$\begin{aligned} TC(X;Y) &= TC(X) - TC(X|Y) \\ &= \sum_{i=\mathbb{N}_n} (I(X_i : Y) - I(X : Y)) \end{aligned} \quad (1)$$

Optimizing over Equation 1 is thus equivalent to searching for a latent factor Y. Let Y be a discrete random variable that can take k values. This optimization may be represented as

$$\max_{p(y|x)} TC(X;Y), |Y| = k$$

This can now be extended to account for multiple latent factors $Y_1, Y_2, \ldots, Y_m$:

$$\max_{G_{j,p(y_j|xG_j)}} \sum_{j=1}^{m} TC(XG_j;Y_j), |Y_j| = k, G_j \cap G_{j' \neq j} = 0$$

For our datasets, we choose 2 hidden units with 4 dimensions each for the computations.

4.3 K-means Clustering on Sentence Vectors

For this third technique, we consider the `Word2Vec` tool which has been introduced by Mikolov et al (Mikolov et al., 2013; Goldberg and Levy, 2014). This tool has played a major role in recent developments in natural language processing. It is a group of related models which is used to produce word embeddings and therefore it gives us a way to represent words in terms of vectors in a real space, while preserving the linguistic context.

The process involves the following steps:

1. Assign a character corresponding to each of the 16 positions, since we have 16-bit binary vectors.
2. For every vector, we keep the words corresponding to ones.This gives us 6-word sentences (or patterns) corresponding to each vector in the dataset, thus forming our working corpus.
3. We now compute word vectors using `Word2Vec` for this corpus.
4. Sentence vectors, which are computed as the averaged word vectors for each sentence, form a new representation for the original binary vector dataset.
5. Since the dataset is now represented in a real space, we can now use classical clustering methods like k-means.

4.4 Final Processing by Majority Vote

Once the three previous clustering techniques have been applied to our dataset, we explore the possibility of combining the partitions we have obtained through these different methods. The aim is to get a better clustering. This attempt is based on a simple majority vote.

For that purpose, all pairs of vectors are taken and each of the three methods is checked to count the total number of times the two vectors were kept in the same cluster. If the count is greater than or equal to 2, we keep the two vectors in the same final cluster. Since the clusters obtained via the three methods lie on different spaces with different centroid, we cannot simply vote on cluster labels. Thus, for each pair of vectors, we see how many methods keep them in the same cluster.

5 EXPERIMENTAL RESULTS

We have been provided with four datasets to analyse denoted $\mathcal{D}_1, \mathcal{D}_2, \mathcal{D}_3, \mathcal{D}_4$ respectively. Let us precise that dataset $\mathcal{D}_1$ has binary vectors of weight 6 (there are 8,008 such vectors at most). It is a special case provided by the French police forces. Table 1 summarizes the parameters for these four datasets.

Table 1: Dataset parameters.

Dataset	Dataset size	# malicious vectors
$\mathcal{D}_1$	4,692	5
$\mathcal{D}_2$	3,802	20
$\mathcal{D}_3$	3,804	5
$\mathcal{D}_4$	3,809	51

5.1 Leading Eigenvector

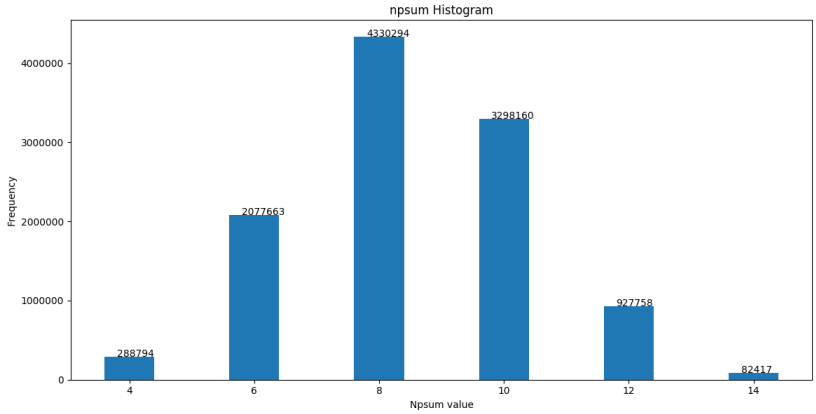
The best results are obtained with npsum_{01}. The structure of the graph (density) and the resulting adjacency and modularity matrices strongly depends on the threshold value we consider. Figures 1 and 2 show the number of edges in the graph modelling each dataset for different threshold values. from the analysis of Figures 1 and 2 we clearly see that only threshold values greater or equal to 12 are likely to provide the expected results. In other words, the graph density is not too high in order to have a chance to get a sufficient number of connected components corresponding to the expected partition. On the other side, a too small threshold (less than 8) would provide also a sparse graph but with too many connected components. As a consequence the useful information would be spilled up and wasted.

Once the clustering step (see Section 4.1) has been applied we obtain four clusters. Table 2 summarizes the results. We can see that dataset $\mathcal{D}_1$ and $\mathcal{D}_4$ give the best results for a threshold value of 14 while datasets $\mathcal{D}_1$ and $\mathcal{D}_4$ give better results with a threshold value of 12. As a general decision rule, the best cluster appears to be obtained by taking the largest cluster at the end of clustering phase 1 and then the smallest cluster at the end of the clustering phase 2.

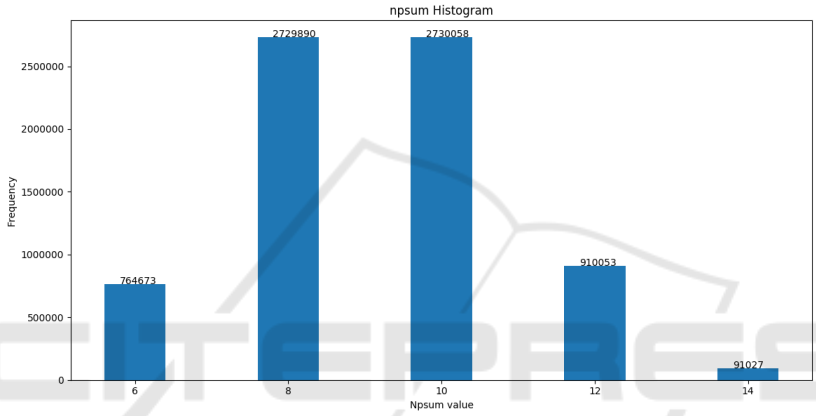
5.2 The Correlation Explanation Method

We applied the clustering in two steps as in the previous method. We obtain the results presented in Table 3.

As a general rule, we can decide to keep the largest cluster but with a residual error of 0.25. However it is admitted that the four resulting clusters can be post-processed in parallel.



$\mathcal{D}_1$



$\mathcal{D}_2$

Figure 1: *npsum_01* Thresholds value vs Number of Edges (datasets $\mathcal{D}_1$ and $\mathcal{D}_2$).

Table 2: Partition of datasets with npsum_{01} threshold of 12 (top) and 14 (bottom) (leading eigenvector technique).

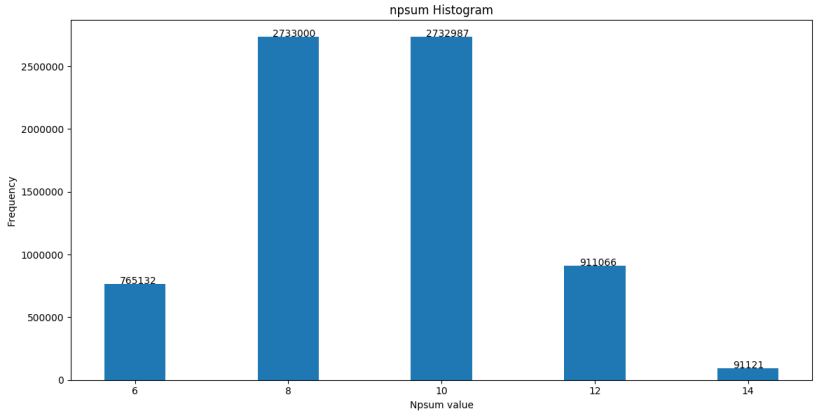
	$\mathcal{D}_1$ - T12		$\mathcal{D}_2$ - T12		$\mathcal{D}_3$ - T12		$\mathcal{D}_4$ - T12	
	Positives	Total	Positives	Total	Positives	Total	Positives	Total
Cluster 0_0	5	1195	7	944	0	920	29	932
Cluster 0_1	0	1126	0	937	1	967	6	991
Cluster 1_0	0	1203	13	904	4	938	0	945
Cluster 1_1	0	1168	0	1017	0	979	16	941
	$\mathcal{D}_1$ - T14		$\mathcal{D}_2$ - T14		$\mathcal{D}_3$ - T14		$\mathcal{D}_4$ - T14	
	Positives	Total	Positives	Total	Positives	Total	Positives	Total
Cluster 0_0	0	1160	1	936	0	925	0	974
Cluster 0_1	0	1167	9	958	3	931	17	927
Cluster 1_0	4	1150	0	996	2	910	12	998
Cluster 1_1	1	1215	10	913	0	1038	22	910

5.3 K-means Clustering on Sentence Vectors

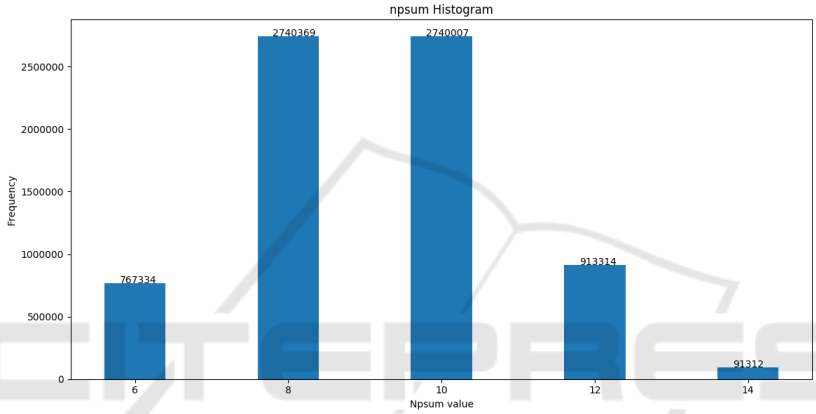
We applied the clustering in two steps as in the two previous method. We obtain the results presented in Table 4. As a general rule, we can decide to keep the smallest cluster.

5.4 Final Processing by Majority Vote

According to the procedure described in Section 4.4, the majority vote scheme has been applied on the four datasets with the following results presented in Table 5. Extracting a general decision rule is not possible from this majority vote procedure, However, it



$\mathcal{D}_3$



$\mathcal{D}_4$

Figure 2: *npsum_01* Thresholds value vs Number of Edges (datasets $\mathcal{D}_3$ and $\mathcal{D}_4$).

Table 3: Partition of datasets with the correlation explanation technique.

	$\mathcal{D}_1$		$\mathcal{D}_2$		$\mathcal{D}_3$		$\mathcal{D}_4$	
	Positives	Total	Positives	Total	Positives	Total	Positives	Total
Cluster 0_0	5	1001	14	1203	0	880	0	1180
Cluster 0_1	0	1781	5	617	5	1190	5	1125
Cluster 1_0	0	745	0	863	0	619	15	625
Cluster 1_1	0	1165	1	1119	0	1115	31	879

Table 4: Partition of datasets with the K-means clustering on sentence vectors technique.

	$\mathcal{D}_1$		$\mathcal{D}_2$		$\mathcal{D}_3$		$\mathcal{D}_4$	
	Positives	Total	Positives	Total	Positives	Total	Positives	Total
Cluster 0_0	3	857	0	912	0	918	35	858
Cluster 0_1	0	1384	16	796	2	1108	12	893
Cluster 1_0	0	1134	4	1201	0	922	0	920
Cluster 1_1	2	1317	0	893	3	856	4	1138

Table 5: Partition of datasets with the cluster ensemble.

	$\mathcal{D}_1$		$\mathcal{D}_2$		$\mathcal{D}_3$		$\mathcal{D}_4$	
	Positives	Total	Positives	Total	Positives	Total	Positives	Total
Cluster 0_0	3	918	0	1141	0	586	47	1068
Cluster 0_1	0	1334	10	1134	0	513	0	951
Cluster 1_0	0	1132	7	614	4	745	0	661
Cluster 1_1	2	1308	3	913	1	1960	4	1129

worth mentioning that when applied, positive vectors are more concentrated in a cluster. It was precisely one strong result to achieve.

6 CONCLUSION

In this paper we have addressed the problem of clustering sparse binary vectors in the field of security. Since the vectors we have to deals with cannot be efficiently clustered by known techniques, the aim was to find a procedure that would systematically cluster data in such a way that one cluster would contain most of the positive vectors describing potentially suspicious terrorist activity. With such a cluster, it is then possible to perform an intelligence-driven post-processing step that is tractable while it is not on the initial sets.

The study presented here considers only four datasets which could be of course considered as non significant on such a reduced number of cases. Our techniques has been transferred to the police entity which was requested this study. Their feedback show that our techniques is still valid and robust when considering vectors of larger length but still sparse.

We hope this study will draw attention from other researchers that would be interested to investigate with other approaches. This is the reason why we have been authorized to share the four datasets used in this study. Anyone interested can contact the first author.

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