Abstract: A public safety answering point (PSAP) receives thousands of security alerts and attends a similar number of emergencies every day, and all the information related to those events is saved to be post-processed and scrutinized. Visualization and interpretation of emergency data can provide fundamental feedback to the first-response institutions, to managers planning resource distributions, and to all the instances participating in the emergency-response cycle. This paper develops the application of multiple correspondence analysis (MCA) of emergency responses in a PSAP, with the objective of finding informative relationships among the different categories of registered and attended events. We propose a simple yet statistically meaningful method to scrutinize the variety of events and recorded information in conventional PSAPs. For this purpose, MCA is made on the categorical features of the available report forms, and a statistical description is achieved from it by combining bootstrap resampling and Parzen windowing, in order to provide the user with the most relevant factors, their significance, and a meaningful representation of the event grouping trends in a given database. We analyzed the case of the 911-emergency database from Quito, Ecuador, which includes 1,078,846 events during 2014. Individual analysis of the first-response institutions showed that there are groups with very related categories, whereas their joint analysis showed significant relationships among several types of events. This was the case for fire brigades, military, and municipal services attending large-scale forest fires, where they work in a combined way. Independence could be established among actions in other categories, which was the case for specific police events (as drug selling and distribution) or fire brigades events (as fire threats). We also showed that a very low number of factors can be enough to accurately represent the dynamics of frequent events.

Keywords: public-safety answering point; first-response institutions; multiple correspondence analysis; ECU-911; Parzen windows; bootstrap resampling

1. Introduction

In order to improve a centralized and opportune emergency response [1], Ecuador created in 2012 the integrated security service, named ECU-911 [2]. Within its structure, a Public Safety Answering Point (PSAP) is a center in which emergency alerts are received and processed. If an alert is classified...
as an actual emergency by the PSAP, some of the First Response Institutions (FRIs), i.e., fire brigades, police, health services, transit agency, and others, will dispatch their units to attend that event. In this case, FRIs and emergency units work under centralized coordination and permanent feedback all the time. In addition, information from all emergencies received by a PSAP is saved on a centralized Data Base (DB). On the other hand, data analysis capabilities are a crucial component of the standard model of Emergency Response Systems [3]. Knowledge management is an additional factor which uses information from previous experiences to improve emergency responses, their procedures, and their normative [4]. However, when reviewing the information from the DB in integrated security services, we often find descriptions based on a mixture of quantitative and categorical variables. In the first case, it is feasible to apply statistical techniques to obtain the information that we need to feedback to the FRIs. In the second case, the use of traditional statistical tools and techniques could become hard and complex.

Some previous works have already tackled the problem of emergency response systems and how data analysis can help to improve them. For instance, an overview was presented in [2] of how technology can support several new models of emergency attention services based on Enhanced-911 platforms. The idea of data treatment and analysis is also discussed therein, but no real analysis is actually performed. In the same line, Jennex proposed a model for emergency response systems [4]. This work suggested that there are failings in emergency response systems that knowledge management could prevent, or at least mitigate. However, no knowledge management system is proposed or evaluated therein. Moreover, a data model is also proposed in [5,6] for the management of dynamic data during emergency response procedures in the Netherlands. Their spatio-temporal model allows to maintain operational and situational information in emergency response, but the model was never proven as an input for analyzing or inferring emergency behaviours. There are some other works oriented to specific analyses of emergency responses, like sentiment analysis during a hurricane [7] or response-time analysis of subway fire emergencies [8]. Liu et al., in [9,10], proposed risk decision analysis methods based on cumulative prospect theory and fault tree analysis, respectively, to solve the risk decision-making problem in emergency responses. Emergency evacuation from barrier lake downstream villages and H1N1 infectious diseases, respectively, illustrated the proposed methods. Unlike these specific analyses, our interest is oriented to emergencies reported by a 911-like service, looking for a more general and simpler approach. Previous works have also proposed spatio-temporal analysis of emergency alerts. For instance, Jasso et al. [11] presented a spatio-temporal analysis of call-stream data corresponding to emergency responses in the State of California. This work points to the possibility of emergency event detection based on outlier detection. In the same direction, [12] proposed a statistical, spatial, and temporal analysis of emergency responses by using simple, yet robust and compact, event representations.

In order to reach a better understanding of the existing qualitative information, we propose here a method that, while maintaining its simplicity, allows us to obtain statistically meaningful results and to support the managers to inspect the emergencies attended by FRIs, through the analysis of the reports routinely stored in the PSAP DB. By applying Multiple Correspondence Analysis (MCA) techniques to the FRIs considered as grouping variables, and to the emergencies attended as categories, we hypothesize here that we can obtain even an improved statistical description if we combine them with bootstrap resampling techniques and Parzen windowing. A precedent of this type of principled analysis was proposed in our previous contribution in [12], which allowed to systematically obtain statistical, temporal, and spatial information for emergency events. In this setting, we now obtain relevant information, its statistical significance, and intuitive 3D representations of the trends and relationships of the information taken from the DB, which is compatible with a rigorous statistical background and description of the characteristics of the events. We scrutinized the usefulness of the proposed method in the analysis of patterns and similarities in the events recorded in the city of Quito (Ecuador). Our analysis paid attention to different FRIs, either individually or jointly considered, and to a comprehensive set including most of the relevant emergency categories in the ECU-911 DB.
that were stored during 2014. Note that the proposal in [12] for statistical, spatial, and temporal analysis of emergency responses is then extended here by making use of multiple correspondence analysis, to complete our knowledge and to figure out relationships among events, besides their spatio-temporal performance.

The rest of the manuscript is organized as follows. Section 2 explains the motivation for this research. Section 3 discusses the MCA analysis used in our study. Section 4 explains the origin and characteristics of the DB used for this research. Section 5 specifies the DB reading procedure and its graphical analysis. Section 6 provides a summary of the main results obtained using MCA and its statistical extension with bootstrap resampling and Parzen windowing. The most relevant results are discussed in Section 7. Conclusions and recommendations for future implementations are presented in Section 8.

2. Motivation

In order to explain the emergency response cycle, let us start defining an emergency as a high-stress situation that requires organizations to respond in a different way from their usual operational procedures [4,13]. Figure 1 shows a diagram of the FRI activity level along time. We can clearly identify four phases and five decision points that characterize an emergency [4]. During the Situational Analysis (SA) phase, the alert mechanisms of a PSAP are prepared to receive alerts. Once an alert becomes into an emergency, an Initiating Event (IE) point occurs in \( t_1 \), the emergency information is transferred to the FRI dispatcher, and the Initiation Response (IR) phase begins. In \( t_2 \) or Control Event (CE) point, the Emergency Response (ER) phase starts, and the FRI activity increases due to the resources moved and deployed to the affected area. In \( t_3 \) or Restoration Event (RE) point, the emergency is under control and part of the displaced units return to their operational bases. Only the strictly required FRIs remain operative and supporting the affected area during this Restoration Response (RR) phase. Finally, in \( t_4 \) or Normalizing Event (NE) point, all units return to its normal activities, and the emergency response cycle automatically restarts with a new SA phase. At any time of the emergency, and according to the circumstances, it is possible to finish it by jumping directly to the Termination Event (TE) point, and for that reason, this point is not vertically located in the plot timeline. All the analyzed emergencies occur during ER and RR phases of the represented figure, and they are subsequently assigned to a set of possible categories taking place in the mentioned phases.

![Figure 1. Representation of the First Response Institution (FRI) activity level along time when an emergency is detected. Activity level has four phases (Situational Analysis (SA), Initiation Response (IR), Emergency Response (ER), Restoration Response (RR)) and five decision points (Initiating Event (IE), Control Event (CE), Restoration Event (RE), Normalizing Event (NE), Termination Event (TE)) [4].](image)

The PSAP-attended emergencies are daily saved in a local DB from which a centralized Data Warehouse consolidates the information countrywide [2]. By using suitable statistical techniques, this information could be analyzed in order to obtain relevant feedback for all the service and articulated institutions, and this information will undoubtedly be of capital importance to feedback the institutions involved in the emergency response process. This analysis will permit us to understand how emergency processes work and to visualize how the FRIs operate for each type of emergencies that they attend. In this direction, we propose the use of MCA applied to FRIs, emergencies, and categories that are
recorded in the emergency forms, in order to find out the possible relations among them with an easy-to-handle, yet statistically rigorous system. MCA is often used with other well-defined and well-known analysis purposes in marketing sciences, notwithstanding that with this unusual and novel application of MCA, we expect to find additional judging elements to evaluate the general results of FRIs in the emergency response field.

3. MCA Statistical Characterization

Due to the amount of information stored in the DB, it is necessary to find techniques that simplify the visualization of the events, especially if an emergency has the participation of more than one FRI. In this paper, we propose the use of an extended MCA in the emergencies attended for a PSAP, which allows straightforward 2D and 3D visualizations of the events, their relationships, and their statistical variability. MCA is a variation of Correspondence Analysis (CA) that permits us to observe and analyze the relationship among several categorical (and to some extent mutually dependent) variables [14]. CA is an exploratory multivariate technique for graphical and numerical analysis that can be used with almost any data matrix with non-negative entries, but it is most widely used when studying contingency tables or count tables [15]. Specifically, MCA can be used when several categorical variables are considered and when they are organized as a matrix with entries given by zeros and ones, this binary code representing the values that a set of categorical variables adopts for a set of their measurements in a population of individuals.

In order to better understand the applied procedure, we present the following two subsections. First, a summary is given on the matrix fundamentals of MCA for categories, which presents the basic elements of the method used in the present work. Second, the principles of the Bootstrap resampling techniques are briefly presented, which provide us with the joint distribution of different categories in the MCA case. After that, Parzen windowing is used to characterize the multidimensional confidence area, yielding a tool that is similar to the confidence interval applied in a unidimensional analysis, but here allowing us to visualize the different categories and when they can be significantly differentiated or statistically overlapped in a multidimensional probabilistic space.

3.1. Matrix Fundamentals of MCA

Let us consider the number of FRIs as \(k_n\) categorical variables, so that each of them has \(J_{k_n}\) categories, with \(J_{k_1} + J_{k_2} + \ldots + J_{k_n} = j\). There are \(I\) emergencies registered in the DB, and the \(I \times J\) indicator matrix is denoted by \(X\). By applying CA on \(X\) we obtain two sets of factor scores, one for the rows and another for the columns. The total obtained from the table is noted as \(M\), which is the sum of both the rows and the columns of the \(X\) matrix. To obtain the probability matrix \(Z\), we use \(Z = M^{-1}X\). On the other hand, \(r\) is the vector of the row totals of \(Z\) and \(c\) is the vector of the column totals, and \(D_c\) (\(D_r\)) is the diagonal matrix of \(c\) (\(r\)). The factor scores are obtained with the following singular value decomposition:

\[
D_r^{-\frac{1}{2}}(Z - rc^T)D_c^{-\frac{1}{2}} = P\Delta Q^T
\]

where \(\Delta\) is the diagonal matrix of the singular values, and \(\Lambda = \Delta^2\) is the matrix of the eigenvalues. The row and column factor scores are obtained with the relations,

\[
F = D_r^{-\frac{1}{2}}P\Delta \\
G = D_c^{-\frac{1}{2}}Q\Delta
\]

The squared distance \((X^2)\) from the rows and columns to their respective barycenter are obtained with the equations

\[
d_r = \text{diag}\{FF^T\} \\
d_c = \text{diag}\{GG^T\}
\]
and squared cosine between row $i$ and factor $l$ and between column $j$ and factor $l$ are obtained as:

$$O_{i,l} = \frac{f_{i,l}^2}{d_{r,i}^2}$$  \hspace{1cm} (6)

$$O_{j,l} = \frac{g_{j,l}^2}{d_{c,j}^2}$$  \hspace{1cm} (7)

where $d_{r,i}^2$ and $d_{c,j}^2$ are the $i$-th element of $d_r$ and the $j$-th element of $d_c$, respectively. The squared cosines help locating the factors that are important for a given categorical variable. The contributions of row $i$ to factor $l$ and of column $j$ to factor $l$ are calculated with

$$t_{i,l} = \frac{f_{i,l}^2}{\lambda_l}$$  \hspace{1cm} (8)

$$t_{j,l} = \frac{g_{j,l}^2}{\lambda_l}$$  \hspace{1cm} (9)

where $\lambda_l$ are the eigenvalues obtained form the indicator matrix. These contributions help us to identify the observations or variables that are important for a given factor.

By using the transition formula, the supplementary or illustrative elements can be projected onto the factors. Let us consider $i_{sup}^T$ as an illustrative row and $j_{sup}^T$ as an illustrative column to be projected. Their coordinates $f_{sup}$ and $g_{sup}$ are obtained as

$$f_{sup} = (i_{sup}^T1)i_{sup}^TG\Delta^{-1}$$  \hspace{1cm} (10)

$$g_{sup} = (j_{sup}^T1)j_{sup}^TF\Delta^{-1}$$  \hspace{1cm} (11)

By applying CA to the indicator matrix, the factor scores are provided for the rows and the columns. However, these factor scores need to be re-scaled for MCA. The $J \times J$ table given by $B = X^TX$ is the so-called Burt Matrix associated to $X$. This table is relevant in MCA because using CA on the Burt matrix gives the same factors as the analysis of $X$ but it is often computationally easier to calculate. The Burt matrix also plays an important theoretical role, because the eigenvalues obtained from its analysis give a better approximation of the inertia explained by the factors than the eigenvalues of $X$ [14].

When analyzing the MCA results, it is necessary to use different mathematical elements to evaluate them and reach conclusive results. The most frequently used metrics are briefly explained next [16]. Inertia is an information measure that shows the data dispersion around the gravity centre. Total inertia stands for the inertia of all the variables and categories analyzed, and it is necessary to represent the presence or absence of the events in the DB with ones and zeros, respectively. Relative inertia is the inertia of each variable in each dimension, it needs to be normalized between 0 and 1, and it represents all the information of a variable in all the dimensions. It can also be seen as the contribution of each variable. Eigenvalues represent the relative relevance of each dimension to the total inertia associated to their specific directions as multivariate vectors. We usually find the highest eigenvalue in the first direction, and they decrease in the following direction. Eigenvalues and accumulated inertia are parameters often used to select the dimensions to be included in the MCA result. The final objective of using MCA is to reduce the number of dimensions to represent the majority of the information contained in the Burt matrix and to represent them with the minimum number of dimensions as possible.

3.2. Bootstrap Resampling and Parzen Windowing

We analyzed the statistical distribution of the projection of each column in the previous MCA formulation, which corresponded to the categories of the events contained in the DB. By using
Bootstrap resampling techniques, we can obtain a cloud of points that implicitly contain their empirical distribution in the projected space, and the subsequent generation of confidence regions through Parzen windows allows the compact representation of those regions. In this way, regions of confidence that overlap will indicate significant statistical relationship among those categories analyzed, and regions of confidence not overlapping each will point towards independent event categories.

A Bootstrap resample of a given list of statistical measurements \([17,18]\) is obtained by generating a new list of measurements from sampling with replacement of the original list \([19]\). In this case, if the operator yielding the coordinates of the projection of an illustrative column from the data matrix is denoted by \(\Gamma\), we can write it as follows:

\[
g_{\text{sup}} = \Gamma(X)
\]

(12)

We can also denote its corresponding column eigenvalue as \(v\), and denote by \(\Theta\) the operator yielding it from the data matrix, i.e.,

\[
v = \Theta(X)
\]

(13)

Now we denote the resampled data matrix \(X^*\) as the result of sampling with repetitions its rows up to \(I\) times, so that it has the same size as the original data matrix. A bootstrap replication of a statistical measurement is obtained by calculating that measurement on the resampled population, instead of the original one, so that we can resample at a given iteration both the projection of a column and the eigenvector,

\[
g_{\text{sup}}^*(b) = \Gamma(X^*(b))
\]

(14)

\[
v^*(b) = \Theta(X^*(b))
\]

(15)

where asterisk * indicates the usual notation in Bootstrap resampling for statistical elements coming from the plug-in principle and resampling process, to distinguish them from the empirical or theoretical statistical elements. Note that the resampled data matrix contains rows of the original ones appearing zero, one, or several times. In the previous equations, \(b\) indicates the number of resamples that we are building. After resample \(b\) is built, a Bootstrap replication can be built for the statistical distribution of any of the described statistical elements \([12,17]\). The resampling and replication processes are repeated \(B\) times (typically \(B = 50, 100, 200,\) or \(500\) times), which provides an estimation of the empirical distribution function of the statistical element. This procedure can be extended to all the eigenvectors and to all the categories, which allows us to determine their empirical distribution. It is easy to construct confidence intervals for the eigenvectors, as will be seen in the next section. However, the multidimensional distribution of different projected categories is given by a set of point clouds, one cloud per category, which can not be readily visualized in this form.

In 1962, Parzen introduced a non-parametric method that can be used for estimating probability density functions \([20,21]\). In our case, we can consider that a subset of three projected categories (denoted compactly as \(R^*(b) = (g_{n,\text{sup}}^*(b), g_{n,\text{sup}}^*(b), g_{o,\text{sup}}^*(b))\)) is an event series of independent and identically distributed observations, then the empirical probability density function is

\[
p_E(R^*) = \sum_{b=1}^{B} \delta(R - R^*(b))
\]

(16)

We can use a kernel function to give a continuously supported estimation of the probability density function. For instance, the use of the Gaussian kernel often yields a good-quality estimator by virtue of the Central Limit Theorem \([22,23]\), and in this case, the estimated distribution is expressed as

\[
\hat{p}_G(R^*) = p_E(R^*) \ast G(R^*)
\]

(17)
where \( \ast \) denotes the multidimensional convolution operator, and \( G(R^\ast) \) denotes the multidimensional Gaussian kernel, using a common variance \( \sigma^2 \) for all the dimensions and scaled to integrate unity. This kernel width is a free parameter to be chosen according to the observation scale and the number of events. After we have built the Parzen density estimator, we can determine the ellipsoid volume that contains 95% of the point cloud provided by the Bootstrap resampling process.

### 3.3. Toy Example of Proposed Modified MCA

In this section, we present a toy example in order to illustrate the basic elements of the adapted MCA and to give an idea of its theoretical background. Let us assume that we have three categorical variables (FRIs) with two categories each (attended emergencies). In total there are 6 categories that can be present in the same case, either individually or jointly. The generation of a toy example is done by assigning a probability of occurrence to each category, considering both individually and jointly among them in order to observe mutual dependences. For simplicity, the probability of individual occurrence for each variable is the same, and we set it as

\[
P(V_i = \text{cat}_{ij}) = 0.155, \quad \forall i, j
\]  

(18)

whereas the joint-occurrence probability between pairs of categories is set to observe higher and lower probabilities, as follows,

\[
P(V_2 = \text{cat}_{2B}, V_1 = \text{cat}_{1B}) = 0.0275
\]

(19)

\[
P(V_2 = \text{cat}_{2B}, V_3 = \text{cat}_{3B}) = 0.0275
\]

(20)

and

\[
P(V_1 = \text{cat}_{1A}, V_1 = \text{cat}_{1B}) = 0.005
\]

(21)

\[
P(V_1 = \text{cat}_{1A}, V_3 = \text{cat}_{3A}) = 0.005
\]

(22)

In order to show the effect of new occurrences on the obtained eigenvectors, we propose to scrutinize two different situations. In Case 1 we introduce the next occurrence,

\[
P(V_1 = \text{cat}_{1B}, V_2 = \text{cat}_{2B}, V_3 = \text{cat}_{3B}) = 0.005 \quad \text{(Case 1)}
\]

(23)

which reinforces the simultaneous occurrence of the three members of the group created in Equations (19) and (20). In Case 2, we introduce the following type of occurrence,

\[
P(V_1 = \text{cat}_{1A}, V_2 = \text{cat}_{2A}) = 0.005 \quad \text{(Case 2)}
\]

(24)

and hence we create the second group of low probability by including one of the categories in the first group.

Figure 2 shows an schematic of these tree different configurations and the results when using the proposed bootstrapping and Parzen techniques on the eigenvectors obtained from MCA. It can be observed that the group with larger occurrence probability (categories with points in green, red, and blue) overlap between them. Specifically, \( \text{cat}_{2B} \) (red points) is the linkage with the other two categories, and for this reason \( \text{cat}_{3B} \) (green points) does not overlap \( \text{cat}_{1B} \) (blue points). In Case 1, where the occurrence is joint among these three categories, we can check that they actually overlap, regardless of their low probability. We can also check that despite the categories in blue and green points have the same joint probabilities with the category in red points, the blue one is not so much overlapped as the green one. This is due to the existence of a non-null occurrence between this category and the dark blue.
Figure 2. Schemes of the three situations to be scrutinized in the toy example (a,c,d), where $V_i$ with $i = 1, \ldots, 6$ is the $i^{th}$ variable and $\text{cat}_{ij}$ with $i = 1, \ldots, 6$ and $j \in \{A, B\}$ the $j^{th}$ category corresponding to the $i^{th}$ variable. The joint probability of occurrence is shown with a line of different thickness according to its value. The individual probabilities are obviated, as they are equiprobable. In (b,d,f) the projections of the original vectors onto the three most significant eigenvectors are depicted together with their Bootstrap-Parzen confidence regions for each category.
In order to further scrutinize this separation effect of the variable in blue points, in Case 2 we can check that the category in blue asterisks tends to be about the center of the newly created group, whose members are the categories with asterisks and with blue points. Moreover, the category with blue points slightly separates apart from the categories with points, and it slightly closes to the category in blue asterisks.

Figure 3a shows the analysis of the bootstrapped eigenvectors in terms of their confidence intervals. Vertical red lines correspond to those categories affecting (with a 95% confidence interval) to eigenvector $v_i$, $\forall i = 1, \ldots, 6$. As can be seen, the first two situations (Original and Case 1) are strongly similar, with some difference in eigenvector $v_3$, where in Case 1 the category 1B does not seem to affect that much to said eigenvector.

![Figure 3a](image)

Figure 3. Details of the toy example. (a) Analysis of the obtained eigenvectors in the three cases of the toy example and their bootstrap confidence intervals. (b) Eigenvalues for the three cases. (c) Projections of the different occurrences on the eigenvectors. The 6 lines represent the 6 dimensions of the eigenvectors, which cross through each of the categories taking place individually and represented by points and asterisks. Crossed triangles represent the joint occurrences of categories represented by their colors. These joint occurrences are in the subspace delimited by the lines from each of the involved categories in the linear combination of said categories.

Note that the visualization of the eigenvectors in Figure 2b,d,f only used the three first eigenvectors. These are the most significant ones, as we can check in the eigenvalue plots on Figure 3b, where the eigenvalue profiles are very similar in the three cases. Figure 3c shows the projection of each of the different occurrences in the database of the Original case onto the obtained eigenvectors. Though those categories with red, green, and blue points (which belong to the highest-occurrence group) are closer among them, it is hard to get useful information from the database. One of the reasons is that there are
so many new combinations as types of joint occurrence can be present, which can generate a dramatic growing of the representation complexity, which makes this kind of representation little practical. This reinforces the hypothesis that it is more useful to visualize the bootstrapped eigenvectors than the projections of the data onto the obtained eigenvectors.

4. Emergency DB

In this research, we used information from the DB of events occurred during 2014 in the city of Quito attended by the ECU-911 service, consisting of 1,078,846 emergencies distributed in time as shown in Table 1. The DB is composed of 121 fields with entries provided during the emergency attention process. To better group this information, we considered two types of variables according to their kind of information. First, operative information refers to the emergency details like alert mechanism, the identity of involved persons, type of emergency, locations, time, date, province, moved resources, or contacted PSAPs, among others. On the other hand, control information is used for internal control and quality of service (QoS) purposes inside the Integrated Security Services or in the respective Institution. Here we can find internal codes, times of transfer, assigned dispatch, time of arrival to the event, time of emergency close, a summary of used resources, and others. In our case, the variables are the First Response Institutions (FRIs), namely, Fire Brigades (FB), Risk Management Secretary (RMS), Military (M), Police (P), Health Services (HS), Municipal Services (MS), and Transit (T). Their categories are given by any of the 127 possible events attended by FRIs along time. Table 3 shows the categories when ordered according to their percentage of occurrence. Note at this point that the Categories (C) are given here by the specific type of emergencies attended by each FRI, for instance, fire brigades has 15 categories, as can be observed in Table 2.

Table 1. Emergencies attended by the Public Safety Answering Point (PSAP) of Quito in 2014.

| Order | Month     | Emergencies |
|-------|-----------|-------------|
| 1     | January   | 74,358      |
| 2     | February  | 70,010      |
| 3     | March     | 88,119      |
| 4     | April     | 86,192      |
| 5     | May       | 91,265      |
| 6     | June      | 84,627      |
| 7     | July      | 89,300      |
| 8     | August    | 98,531      |
| 9     | September | 99,878      |
| 10    | October   | 94,322      |
| 11    | November  | 93,897      |
| 12    | December  | 108,347     |
|       | Total     | 1,078,846   |

We applied a data prepossessing stage to filter the valid data before applying MCA. One should note that an event could be reported for more than one alert call, in other words, several institutions could be required to be dispatched in order to attend a specific emergency. Table 4 shows the participation of emergencies attended by each FRI during 2014. Police had a higher participation percentage, followed by Health Services and Transit, Fire Brigades comes next, and with significantly lower participation, they are followed by Municipal Services, Military, and Risk Management Secretary.

From the seven FRIs coordinated by our PSAP, we considered its participation percentage as shown in Table 4, the information detailed in Table 3, and the results of temporal analysis described in [12]. This allowed us to divide the institutions into two groups. The first group, with four FRIs and 95% of the emergencies registered, included Police (45 event categories), Health Services (41), Transit (13), and Fire Brigades (3). The second group, with three FRIs representing 5% of the events, included Municipal Services (8), Military (2), and Risk Management Secretary (3). Starting from this taxonomy, we analyzed the relationships inside each FRI, among institutions, and among categories.
It is important to note that 94 categories had participation below 1% of the total number of the studied events, and some of these categories did not register any event. The information presented in Table 3 allows us to set a percentage of occurrence in order to scrutinize only the representative categories for each case.

Table 2. Categories or specific emergencies considered in the Data Base (DB) for Fire Brigades and its percentage of occurrence.

| Order | Specific Emergency or Category | Occurrence |
|-------|--------------------------------|------------|
| 1     | Structural Fires               | 24.63%     |
| 2     | Fire Rescue                    | 18.12%     |
| 3     | Rescue                         | 17.69%     |
| 4     | Forest Fires                   | 12.86%     |
| 5     | Gas Leaks                      | 9.71%      |
| 6     | Floods                         | 5.99%      |
| 7     | Open Department                | 3.93%      |
| 8     | Hazardous Material             | 3.20%      |
| 9     | Vehicular Fire                 | 2.68%      |
| 10    | Personal or Accident Material  | 0.39%      |
| 11    | Close Hydrant                  | 0.33%      |
| 12    | Unit crashed                   | 0.17%      |
| 13    | Vehicular                      | 0.17%      |
| 14    | Water supply                   | 0.09%      |
| 15    | Domiciles                      | 0.04%      |

Table 3. Categories (C) ordered by their percentage of participation in each First Response Institution (FRI).

| FRIs | C ≥ 30% | 30% > C ≥ 20% | 20% > C ≥ 10% | 10% > C ≥ 5% | 5% > C ≥ 1% | 1% > C | Total |
|------|---------|---------------|---------------|--------------|-------------|--------|-------|
| FB   | –       | –             | 3             | 2            | 3           | 6      | 15    |
| RMS  | –       | –             | –             | –            | –           | 3      | 3     |
| M    | –       | –             | –             | –            | –           | 2      | 2     |
| P    | 1       | –             | 1             | 4            | 7           | 32     | 45    |
| HS   | 1       | 1             | 2             | 1            | –           | –      | 36    |
| MS   | –       | –             | –             | –            | –           | 8      | 8     |
| T    | 1       | –             | 2             | 1            | 2           | 7      | 13    |
| # Cat.| 3       | 2             | 8             | 8            | 12          | 94     | 127   |
| Total% | 31.78% | 3.99%         | 20.06%        | 21.29%       | 12.70%      | 10.18% | - -   |
| Cum.% | 31.78% | 35.77%        | 55.83%        | 77.13%       | 89.82%      | 100%   | - -   |

5. Statistical and Graphical Interpretation

Figure 4 illustrates the procedure designed to obtain MCA and its operative and statistical representations from the event DB. A specific time period is read (e.g., a month) and then we select those variables of our interest. Data preprocessing starts by replacing the event name contained in the DB with a binary code to be used in MCA. It is convenient to set a minimum percentage of participation to hide unnecessary or low represented categories of events, given that keeping the most representative categories yields more statistically accurate results. As explained, the data matrix is resampled, yielding a cloud of replicated projections of the categories on the eigenvector space, and with this data, confidence regions are estimated by using Parzen windowing techniques as explained.
Figure 4. Flowchart of the extended Multiple Correspondence Analysis (MCA) applied to the emergency Data Base (DB).

For better making our visual analysis, the results are presented in three different types of representations, as explained next for the case example of fire-brigade events in Figure 5. We have filtered the number of categories represented, in such a way that those with participation below 0.1% of the total were hidden, thus leaving only six categories. Panel (a) depicts a diagram of six normalized eigenvalues, which represent the relevance of the information contained by each eigenvector. Note that in this case, values above 0.9 provide more relevant information than the others, but it is not easy to establish a threshold. Panel (b) is a graphical representation of the obtained projection directions, constrained in this case to be 6. The use of bootstrap resampling allows us to determine which categories are relevant for each factor (vertical red lines in these subpanels). We can interpret each eigenvector as a factor combining the weighted presence of the different categories. Panel (c) shows the joint projections of the categories on the three first directions, together with the point cloud yielded by bootstrap resampling and the confidence regions yielded by Parzen windowing. We immediately note the bootstrapped concentrations, which in some cases are well defined, and in other cases, they spread out without any recognizable pattern. Nevertheless, some of the confidence regions are clearly separated from the others, indicating their independence, and others overlap with neighbours, indicating their mutual statistical dependence.

Based on these types of plots, it is necessary to define the minimum criteria to select the most representative eigenvectors, which we set to the following: (i) The point concentration located in the positive or negative plane has to be at least 0.1 units separated from 0; (ii) The width of the confidence area has to be equal or narrower than 0.3 units; and (iii) The corresponding eigenvalue has to be equal or larger than 0.9 units. When we address these criteria, the selected eigenvectors will be the ones that best represent the analyzed categories.
Figure 5. Example of reading the results from extended MCA in fire brigades: (a) Eigenvalues represent the importance of each eigenvector. (b) Eigenvectors and their confidence intervals, where the x-axis represents the number of categories included in the data matrix, and the y-axis is the amplitude of that category in the projected subspace. (c) Joint representation of the projected categories and their confidence areas, with respect to three eigenvectors, and their paired view projections.

For a better understanding of the method, here we show the paired views of the projected categories with the first three eigenvectors, as shown in Figure 6. For the first dimension, we use the two plots that contain projection $v_1$, so that these are $v_1 - v_2$ and $v_1 - v_3$. In both 2D views, a vertical red line is traced to separate the negative and the positive regions. Then we locate the category concentrations following their order of participation in the eigenvector. Starting with category 1 (Rescue), the blue concentrations are located in the negative side of $v_1 - v_2$ and $v_1 - v_3$ projections, hence, a blue arrow is traced simultaneously from both projections to the eigenvector plot located below. The head of two arrows intersects on the first projected category, and it verifies that it is located in the negative region of the eigenvector, which is marked with number 1 on the horizontal axis. We complete this procedure with the five remaining categories to obtain the remaining panels.
Figure 6. Fire-brigade categories and relation between paired projected categories plots and their eigenvectors: (a) Detail on eigenvector \( v_1 \), and projected categories in terms of \( v_1 \) and \( v_2 \) (left), and of \( v_1 \) and \( v_3 \) (right); (b) Detail on eigenvector \( v_2 \), and projected categories in terms of \( v_1 \) and \( v_2 \) (left) and \( v_2 \) and \( v_3 \) (right); (c) Detail on eigenvector \( v_3 \), and projected categories in terms of \( v_1 \) and \( v_3 \) (left) and of \( v_2 \) and \( v_3 \) (right).

6. Experimental Results

In this section, we present the results of applying the extended MCA to the FRI information, according to specific grouping parameters for the institutions. As reported in Table 4, when the participation of each FRI in the emergency attention is ordered, Police has the majority presence with 64.2%, Health Services 15%, Transit 12.8%, Fire Brigades 3%, Municipal Services 2.8%, Military 1.3%, and Risk Management Secretary 0.9%. By comparing this information with Table 3 we obtain four main FRI combinations to be scrutinized with detail, as illustrated in Table 5: (i) One FRI at a time to find possible relations among its own categories (we did not consider here RMS, M, and MS); (ii) Groups of FRIs, to observe if there are relations between institutions and categories; (iii) The analysis of the most represented FRIs, to find any relationship or general patterns in them; and (iv) The analysis of the least represented FRIs, to find any relationship or informative patterns in them.
Table 4. Percentage of emergencies attended during 2014, and the number of categories per each FRI in Quito PSAP.

| Order | FRI          | Participation | Categories |
|-------|--------------|---------------|------------|
| 1st   | Police       | 64.2%         | 45         |
| 2nd   | Health Services | 15.0%      | 41         |
| 3rd   | Transit      | 12.8%         | 13         |
| 4th   | Fire Brigades | 3.0%          | 15         |
| 5th   | Municipal Services | 2.8%   | 8          |
| 6th   | Military     | 1.3%          | 2          |
| 7th   | Risk Management Secretary | 0.9% | 3          |
| Total |              | 100.0%        | 127        |

Table 5. FRIs combination to obtain Multiple Correspondence Analysis (MCA) results.

| FB   | RMS | M    | P    | HS   | MS   | T    |
|------|-----|------|------|------|------|------|
| (i)  | -   | -    | (i)  | -    | (i)  | -    |
| (ii) | -   | -    | (ii) | -    | (ii) | -    |
| (iii)| -   | -    | (iii)| -    | (iii)| -    |
| (iv) | (iv)| (iv) | -    | -    | (iv) | -    |

6.1. Individual FRI Analysis

For this type of analysis, each FRI was analyzed separately to find possible relations among its own categories. In this section, we work with the categories or specific emergencies that are detailed in Table 6. Additionally, the categories considered for Military are only three: “Internal defense”, “External defense”, and “Others”. For Municipal Services, seven basic services are considered, i.e., Electric Power, Cleaning and Cleanliness, Potable Water, Sewer system, Other Typification of Cleaning, Parks and Gardens, and Public Works. From all of them, we only used the category “Potable water”.

Table 6. Categories used in the experimental results, ordered by FRIs.

| Fire Brigades | Police                  | Health Services          | Transit                |
|---------------|-------------------------|--------------------------|------------------------|
| 1  Rescue     | Consumption/Drug Sale   | Disease                  | Crashes                |
| 2  Gas Leak   | Public Road Scandal     | Accidental Poisoning     | Collisions             |
| 3  Structural Fire | Suspicious Person     | Traumatism NT            | Vehicle Bad Parked     |
| 4  Fire Conatus | Family Brawl           | Other NT Accidents       | Vehicular Congestion   |
| 5  Forest Fire | Person Requesting Help | Traffic Accidents NT     | Hit by a Car           |
| 6  Open Dept. | Excess of Noise         | Fallen Same Height       | Motorcycle Accident    |
| 7  Floods     | Police Guard            | Violation                | Damaged Vehicle        |
| 8  Hazardous Materials | Non Typified Complaint | Exposure to Cold        | Overturned Car         |
| 9  Vehicular Fires | Theft                  | Run over by a Car       | Closed Way             |
| 10 Close Hydrant | Capture Bulletin       | Wounded Head             | Traffic Light damaged  |
| 11 Pers./Mat. Accident | Escort of Values     | Convulsion               | Fall of a Passenger    |

6.1.1. Fire Brigades

In Figure 7a, six emergencies attended by the fire brigades are illustrated. Observing the eigenvectors plot (first column), and applying the selection criteria described above, it is easy to note that the 1st, 2nd, and 3rd dimensions are the best ones describing the selected categories. Using the first one, we observe concentrations that are well defined and not too spread out. The 3D plot (second column) allows us to visualize all the categories plotted together, whereas in the 2D plot of the selected eigenvectors (third column) we observe concentration of three categories with enough separation between them to interpret them as independent events, and they correspond to ‘rescue’, ‘gas leak’, and ‘open department’. We also observe three overlapped categories with their concentrations circled in red, and they are structural fire, fire threats, and forest fire, making evident a relationship between the
three represented types of fire. Observing the eigenvalues plot (fourth column), we clearly note the relevance of the eigenvector presented, in this case, the 6th eigenvector accomplishes with selection criteria (i) and (ii), but it fails in (iii) because it has a zero eigenvalue, and its relevance is null.

6.1.2. Police

In Figure 7b, 11 categories attended by the police are illustrated. In the eigenvectors panel, we observe that the 1st and 2nd dimensions describe mostly these categories, and we select the first one because it accomplishes all the selection criteria. In the 3D plot, we observe the categories plotted together. In the 2D view, we observe two categories isolated, corresponding to capture bulletin and escort of values. The other nine categories appear overlapped (circled in red), and they are ‘consumption and drug sale’, ‘public road scandal’, ‘suspicious person’, ‘family brawl’, ‘person requesting help’, ‘excess of noise’, ‘police guard’, ‘non typified complain’, and ‘theft’. We can observe the eigenvalues that bring information about the relevance of the eigenvectors. By using this information, we can observe the result of the service escort of valuables provided. The users ask for this service when they need to move money or goods from or to a financial institution when they receive the escort and it acts as a dissuasive element. Supporting this is the fact that events of suspicious person or theft are located in concentrations very separated from the concentration of this service, which verifies its effectiveness.

Figure 7. Individual MCA results of fire brigades, police, health service, and transit. See text for detailed explanation.
6.1.3. Health Services

In Figure 7c, 8 categories are illustrated. We note that the 1st eigenvector is the one that best describes those categories according to the selection criteria. In the $v_1$ plot (third column), we observe three categories that are separated, and these correspond to ‘disease’, ‘accidental poisoning’, and ‘traffic accident’. We also see 5 categories that are grouped together (circled in red), and these are ‘traumatism’, ‘other non-traffic incidents’, ‘fallen from height’, ‘violation’, and ‘exposure to cold’. This spatial distribution allows us to infer the relations among some of these 6 overlapped categories. Observing the eigenvalues plot, we note that only four eigenvectors are above 0.9, so the fifth and sixth eigenvectors are not representative as selection criteria, as indicated by criteria (iii).

6.1.4. Transit

In Figure 7d, 9 transit categories are illustrated. Observing the eigenvectors plot, the 1st dimension is the best one describing the selected categories according to the selection criteria. In the $v_1$ plot, we note three isolated categories, and these are ‘crashes’, ‘bad-parked vehicle’, and ‘closed way’. The other 6 overlapped categories (circled in red) are ‘collisions’, ‘vehicular congestion’, ‘hit by a car’, ‘motorcycle accident’, ‘damaged vehicle’, and ‘overturned car’. We can observe some relation among some of these 6 overlapped categories, and it is interesting that damaged vehicle is the category with the largest spread. Observing the eigenvalues plot, we see that only four eigenvectors are relevant, as their value is above 0.9, and the other two have reduced incidence.

6.2. Combined FRIs Analysis

To analyze the information of institutions combined by pairs, we set a threshold to visualize the categories from both FRIs according to their participation. In Figure 8, we observe four columns of plots, and they correspond to the first eigenvector (first column), 3D plots of the complete categories (second column), the plot of the overlapped categories (third column), and the plot of the unrelated categories (fourth column). The eigenvalues plot was omitted.

6.2.1. Police and Health Services

In Figure 8a, we observe the first eigenvector (which is the most representative one), and 16 categories are plotted together (11 of police and 5 of health services). The four related categories are family brawl (P), person requesting help (P), theft (P), and traumatism (HS). We clearly note that in those 3 police events, there are usually people involved and health services attend to the victims affected with traumatisms in most cases. The less related categories are consumption and drug sale (P), capture bulletin (P), escort of values (P), and traffic accident (HS), which is consistent with the different nature of those events.

6.2.2. Police and Transit

In this case, we obtain 14 categories (11 from police and 3 from transit), as illustrated in Figure 8b. Seven related categories are public road scandal (P), suspicious person (P), person requesting for help (P), non-typified complain (P), crashes (T), bad-parked vehicle (T), and vehicular congestion (T). The less related categories are consumption and drug sale (P), capture bulletin (P), escort of values (P), and crashes (T).

6.2.3. Police and Fire Brigades

In this case, we found 15 categories (14 from police and 1 from fire brigades), as seen in Figure 8c. Related categories are consumption and drug sale (P), public road scandal (P), suspicious person (P), family brawl (P), person requesting help (P), excess of noise (P), police guard (P), non typified complain (P), theft at home (P), theft (P), gun abuse (P) and fire threat (FB). The less related categories are missing people (P), capture bulletin (P), escort valuables (P), and fire threat (FB). Due to the very
low of participation of fire brigades in relation with police, only one category of FB appears as related but with very low incidence.

6.2.4. Health Services and Transit

In this case, we obtain 8 categories (5 from health services and 3 from transit), as seen in Figure 8d. Related categories are traffic accident (HS) and crashed (T), reflecting a logical closer relation. The less relates categories are disease (HS), traumatism (HS), traffic accident (HS), bad-parked vehicle (T), and vehicular congestion (T).

Figure 8. MCA results of paired combinations for fire brigades, police, health service, and transit. Each row shows the first eigenvector, a general 3D plot, a 3D plot of the related categories, and a 3D plot of the unrelated categories (eigenvalue plot is omitted).
6.2.5. Health Services and Fire Brigades

We obtain 11 categories (6 of health services and 5 of fire brigades), as seen in Figure 8e. Related categories are traumatism (HS), other non-traffic incidents (HS), traffic accident (HS), fallen from the same height (HS), rescue (FB), and forest fire (FB). The less related categories are accidental poisoning (HS) and structural fire (FB).

6.2.6. Transit and Fire Brigades

We obtain 11 categories (7 of transit and 4 of fire brigades), as seen in Figure 8f illustrates. Related categories are hit by a car (T), motorcycle accident (T), overturned car (T), and rescue (FB), which is logic because in a traffic accident, usually the fire brigades attend and cut the metal structure of the car to rescue the survivors. The less related categories are crashes (T), bad-parked (T) vehicle, vehicular congestion (T), and structural fire (FB).

We also analyzed the combination of FRIs in a group of three, including health services, transit, and fire brigades. Figure 9a shows the first 6 eigenvectors of the categories, and by applying the selection criteria, the first one is the most representative. Panel (b) shows the 3D plot of 12 categories (5 of health services, 6 of transit, and 1 of fire brigades). Panel (c) depicts two well-differentiated concentrations, where the left one shows a relation between traffic accidents (HS), crashes (T), hit by a car (T), and motorcycle accident (T). In a separate concentration are the points corresponding to fire threat (FB). This distribution is logical and follows the nature of the events of transit and how they are known to be related, whereas hand fire threat does not have any relation with the other four overlapped categories.

We observed a combination of a group of four FRIs, including fire brigades, risk management secretary, military, and municipal services. In Figure 10a we can observe the eigenvectors, and according to our selection criteria, any of these eigenvectors is representative for this group of categories. In Panel (b) we have 3 groups of events overlapped. When a forest fire of big dimensions overpasses the operative capacity of fire brigades, armed forces (Military) are called to move personnel, vehicles, and aircrafts, and at the same time, potable water service (Municipal Services) is alerted as well to...
provide the liquid needed to recharge the bambi-bucket (big capacity recipient) attached to helicopters and tank trucks.

![Figure 10](image1.png)

**Figure 10.** Categories of fire brigades, risk management secretary, military, and municipal services. (a) Eigenvalues of the FRIs analyzed, according to the selection criteria, none of the dimensions are used to describe this group of categories. (b) All the categories plotted together. (c) Events concentrations of three FRIs, when a forest fire overpasses the capacity of fire brigades, then military forces move personnel, vehicles, or aircraft, and municipal services coordinate the water supply for helicopters and tank trucks. (d) The eigenvalues plot shows us the relative relevance of each dimension in MCA.

7. Discussing the Results

The information saved in the DB can be cataloged as data, and by filtering it, we obtain information usable to prepare reports. If we apply one or more types of analysis, i.e., multiple correspondence, spatio-temporal or statistical [12], we obtain knowledge that characterizes the FRIs, the emergencies, their geographical location, the temporal distribution, and periodical behaviour. If this information is given as feedback to the PSAP, the decision level could implement different actions oriented to warn, prevent, relocate resources, modify procedures, or combine resources, all of them oriented to improve the emergency services response, as can be observed in Figure 11.

In the above-mentioned cases, feedback can be considered as an additional element to be taken into account when implementing actions oriented to prevent or to improve the emergency response. In this setting, MCA results are used to identify relationships among emergencies. As an example, let us consider Police and its two specific categories: suspicious person and theft. We observe that these two emergencies are closely related, according to Figure 12, because in most cases, the sighting of suspicious persons has been followed with theft reports. This phenomenon could be considered to modify the response procedures or to relocate police units when this type of alerts arrive at a PSAP.
Figure 11. If the data saved in the DB are processed, they become information, and by applying different types of analysis it can be transformed into knowledge to give feedback to the management, so that the PSAP can take actions oriented to warn the users, to prevent accidents, or to improve the response in case of emergency.

Figure 12. Plots of Police emergencies, the suspicious persons reported are represented in yellow points, and theft reported are represented with orange stars. By analyzing the information shown in the 3D and 2D plots, we infer that the two types of plotted emergencies are very closely related. With this information in mind, decision makers of this institution would consider dispatching personnel when they receive a report of suspicious persons, to prevent the commission crimes against the property or those in which the lives of the involved citizens may be threatened.

When combined institutions are analyzed, emergencies or categories as a person asking for help (police) are represented with green points, transit accident (health services) with brown triangles, and crashes (transit) with yellow stars can be noted to have a close relation, as shown and explained in Figure 13. The concentrated group of persons asking for help is located close to crashes with a similar spreading, and both emergencies are close to transit accidents attended. If this is an usually related behaviour, when a PSAP receives an alert of any of these type of emergencies, it is possible to modify the procedures to attend them under specific conditions as time or geographical location taken when we apply the analysis proposed in [12], and then those taken actions may result in relocated resources, combined resources, or starting a preventive procedure to warn the divers when vehicles are moving under specific conditions, i.e., a holiday, long weekend, local regional event, or similar ones.

By analyzing health services categories as plotted in Figure 14, we can observe traffic accidents and traumatism represented with blue and yellow points, respectively. Note that most of the attended
traffic accidents have a significant relation with traumatisms. If we observe the upper yellow-point concentration, we deduce that there are also reported traumatisms which did not necessarily involve traffic events. In this line, we probably need to re-categorize those events of traumatism implied in transit accidents to differentiate them from those categories of traumatism detected in non-traffic accidents. In few words, this can modify the procedures to save accurate information to refine this type of post-processing analysis.

The described information in the last three analyzed cases represent a clear set of examples of how the managers and decision takers of the Integrated Security Service and the FRIs can use the feedbacked information obtained from the different types of analysis, including the adapted MCA herein and the spatio-temporal or statistical analysis detailed in [12]. In doing so, they can plan the strategy to face new alerts and emergencies, all the time pointing to warn, and prevent or reduce the impact of the different accidents and incidents that originate the alerts.

Figure 13. Representation of person asking for help (police) in green points, traffic accidents (health services) with brown triangles, and crashes (transit) with yellow stars. The three categories or emergencies plotted appear close one to another in both 3D and 2D plots. This distribution of emergencies and the overlapped elliptical shapes lead us to infer that these categories or emergencies types are significantly related.

Figure 14. Representation of health services emergencies related to traffic accidents in blue, and with traumatism events in yellow. We observe that most of the traffic accidents are related to traumatism reported, but not all the traumatism events are related to traffic.
8. Conclusions

In this paper, we applied an extended version of MCA to visualize data consisting of a group of variables and their categories, applied to the Integrated Security Service of Ecuador. We used it to reduce the less-represented directions and to extract information about the related categories and institutions. By using bootstrap techniques, results are inferred by adding statistical information to the analysis made, and finally, the use of Parzen windowing allows us to see ellipsoid or irregular shapes on the 3D plots to identify possible relations with the similar categories. By applying this extended MCA, we obtained three types of graphics, including projected categories showing their spatial distribution, and based on this, we found the existence or absence of relations among the plotted categories. A second product obtained was the eigenvector confidence bands, and using the information displayed on it we can determine which categories are to be considered as relevant. Finally, we observed the eigenvalues plot, which explains the incidence level of each direction.

With these tools, we can identify the most related categories inside a given FRI, and among different FRIs. Extensive analysis and comparisons can be obtained starting from a simple group of categories or comparing a whole set of them. Not only is the analysis process visually intuitive and operative, hence representing a valuable tool for the emergency managers, but it is also based on solid statistical principles under the visualization interface, thanks to the use of non-parametric statistical techniques.

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