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TagEQ-CN: Classification of seismic events based on complex networks

TagEQ-CN: Clasificación de eventos sísmicos basado en redes complejas

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Abstract

Objective: The exploration of seismic signal detection and classification remains a vital area of research, owing to the vast array of signal types, sensor technologies, and vibration sources.
Methodology: The event classification process leverages data pertaining to nodes or locations where seismic events cluster, along with event communities, to enhance accuracy and effectiveness.
Results: The system underwent rigorous testing utilizing signals sourced from the La Rusia station, a vital component of the Colombian National Seismological Network, yielding highly promising results. This system's applicability extends to incorporating new data for automated earthquake annotation and seamlessly recognizing events from diverse sources with remarkable precision.
Conclusions: Operating within a supervised paradigm, the developed system autonomously selects the signal sets used for training and testing the classifier, relieving users of the burden of manual selection.

Keywords: Complex networks, machine learning, semiautomatic signal labeling, seismic events, classification models

Resumen

Objetivo: Realizar detección y clasificación de señales sísmicas continúa siendo un tema de investigación, dada la diversidad de tipos de señales, sensores y fuentes de vibración.
Metodología: Para el proceso de clasificación de eventos utiliza información sobre nodos o lugares que aglomeran eventos sísmicos, así como también comunidades de eventos.
Resultados: El sistema se testeó con señales provenientes de la estación La Rusia que pertenece a la Red Sismológica Nacional de Colombia, con resultados prometedores. La aplicabilidad de este sistema, permite incluir información nueva para la anotación automática de sismos, así como también reconocer automáticamente eventos de otras fuentes.
Conclusiones: El sistema desarrollado se basa en el paradigma supervisado, el usuario no escoge directamente cuál es el conjunto de señales que se utilizan para el entrenamiento y prueba del clasificador.

Palabras clave: Redes complejas, aprendizaje de máquina, etiquetado semi-automático de señales, eventos sísmicos, modelos de clasificación.

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Introduction

In seismology, developments in signal processing and the detection and classification of seismic signals are constantly occurring [1, 2, 3, 4]. The wide spectrum of signal types, sensor technologies, and vibration sources underscores the active and dynamic nature of this research field [5].

A seismogram may be described as the convolution result of three different transfer functions: the functionality of the vibration source, the influence of the material through which the wave propagates, and the sensor's response to vibrations. Additionally, different phenomena can represent vibration sources in the same time period, among which tectonic, atmospheric, and anthropogenic are some of the sources [6]. Several algorithms can perform event detection; however, there are restrictions to the generality of these systems due to the heterogeneous nature of recorded signals. This represents an intriguing area of study within computer science, aimed at developing algorithms that strive for greater generality in signal classification.

Earthquakes can be understood in terms of P and S waves, whose propagation velocities provide valuable insights into the study of such events. Nevertheless, detection remains an ongoing research challenge due to the immense volume of data and signals produced by seismological networks, necessitating the development of an automatic detection system. Diverse systems were developed for signal processing as well as for event detection. These are the two areas of interest in this study. Existing approaches focus on automatic earthquake detection by applying machine learning schemes, a branch of artificial intelligence. Nevertheless, there is a heterogeneity gap due to the amount of information contained in seismic waves. Hence, the diverse array of sensors tasked with recording seismic events gathers information on the various types of earth structures encountered by the waves routed to the sensors, including different seismic events, such as those associated with volcanoes. Therefore, addressing this gap can be crucially linked to the challenge of predicting certain types of seismic events, leading to life-saving measures for several individuals.

This study introduces a prototype system designed for the classification of seismic events within complex networks. This system forms a component of a broader architecture reliant on artificial intelligence (TagEQ) for seismic event classification. An overview of this architecture was initially presented by Leon et al. [7]. The proposed prototype system represents seismic events as a network, offering a richer dataset for automated event classification. This approach enables the utilization of data regarding nodes or locations where seismic events cluster as well as the identification of seismic event communities and other topological characteristics inherent in complex networks. The study introduces TagEQ-CN, a semiautomatic tagging system tailored for seismic signals. This system processes continuous seismograms obtained from a station, utilizing a catalog of seismic events alongside a network representation of these events to automate the signal classification process. A form of annotation is suggested, leveraging event characteristics in relation to the topology of the earthquake network previously established. Supervised machine learning algorithms were incorporated into such a system. Moreover, a corpus of signals was compiled using data gathered from La Rusia station, which is part of Colombia's National Seismological Network, enabling the application of machine learning algorithms. To accomplish this goal, a modular system was devised to generate and annotate feature vectors extracted from seismic event waveforms, along with features derived from the constructed seismic network (an ETL module), as well as to train an automatic classifier derived from annotated signal sets (a training module). Automatic labeling is performed based on node characteristics, such as degree or betweenness, as well as whether the node is part of a group, such as a community within the network.

Methodology

Several types of seismological classifiers have been implemented, such as self-organizing maps [8, 9], vector support machines [10], or neural networks [11], whose aim is to classify only a few types of signals (noise, local,-regional, teleseismic, and blasting earthquakes).

The quest for patterns in the spatial and temporal distribution of seismic events has facilitated the discovery of tectonic plate boundaries, elucidated their movements within the Earth's mantle, and enabled the evaluation of seismic risk [6]. Numerous studies have attempted to identify precursors of notable events by examining foreshocks [12], magnetic variations [13], and gas emissions [14], among others. While highly intriguing, most of these studies yield inconclusive prognostic outcomes. So far, they suggest the potential for reliably forecasting an event within a temporal range of only a few years at best [15].

Several studies exist for spatial patterns in the spatial distribution of seismic events. Abe and Suzuki [16] researched the spatial complexity of seismic event distribution in Southern California, revealing a fractal geometry commonly observed in complex nonequilibrium systems. The utilization of seismic network construction has emerged as a novel approach to studying the spatial and temporal intricacies of seismic activity. Among others, Baiesi and Paczuski [17] established earthquake networks comprising main shocks and aftershocks by connecting events exhibiting high correlation, revealing a scale-free structure within each identified cluster. Moreover, earthquake networks were constructed by Pastén et al. [18] to investigate the impact of the 2015 earthquake in Illapel, Chile, which had a magnitude of Mw = 8.3. Changes were observed in parameters such as average connectivity and intermediation, which fluctuate in response to the incidence of notable events. These findings provide evidence that large events indeed influence the structure of earthquake networks. Similarly, Chorozoglou [19] applied complex networks to detect precursor events before two earthquakes in Greece, demonstrating the feasibility of this method in conjunction with other measures for seismic risk assessment tasks.

Abe and Suzuki [20] suggested that "a small-world network occupies a space between regularity and randomness, akin to the edge of chaos in nonlinear dynamics." This implies that such networks exhibit both random and structured aspects in their interconnections. Based on what was stated by Leon [21], it was discovered that an earthquake network for Colombia exhibits characteristics of a small-world network, which is consistent with the findings of analogous studies conducted in other regions across the globe. [20].

The integration of complex network features into machine learning tasks warrants further examination [22]. Case studies demonstrating automatic data classification tasks using supervised, semisupervised, and unsupervised learning techniques based on features calculated from data representations, such as complex networks, are detailed in [8, 9, 10]. TagEQ-CN proposes a case immersed in the semisupervised framework.

There are several packages available for analyzing and visualizing complex networks, including SNAP, Gephi, and GraphViz. Additionally, Python libraries such as NetworkX, developed at Stanford University, provide such comprehensive functionality. Currently, no software packages or computational frameworks have been identified specifically designed for constructing seismic networks.

This study aims to introduce a modular architecture capable of classifying events by utilizing single-station seismograms alongside a seismic catalog. This architecture applies high-level directives to annotate events and integrates various algorithms for feature extraction, detection, and classification from complex networks. It demonstrates how these components can be effectively integrated into an automatic classification system.

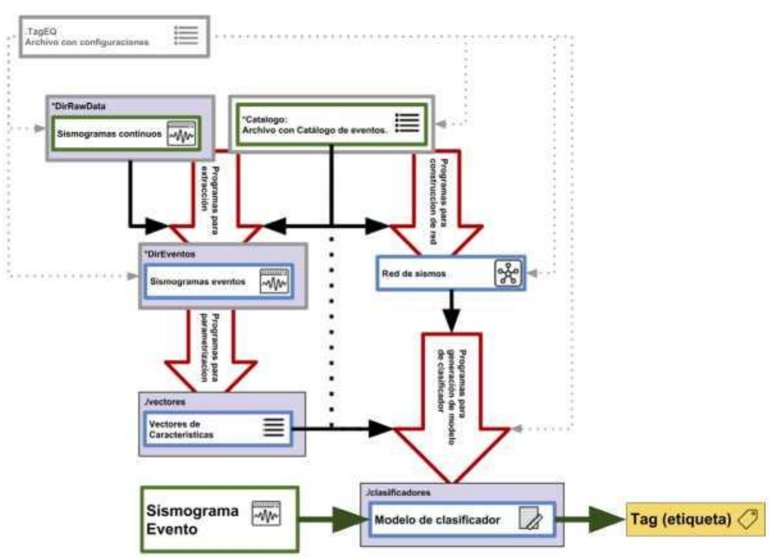
TagEQ-CN Architecture

TagEQ-CN receives a seismic event–annotated catalog with seismograms of a station for a specific time period. This data is used to train a machine learning algorithm. From the seismicity catalog, the system automatically searches for signals corresponding to each event in the seismograms and parameterizes them, generating feature vectors based on information derived from a complex network of earthquakes. This network is constructed based on Lion [21] and divides a region into square cells, where cells containing seismic events are selected as nodes. These nodes are then connected by edges following the temporal sequence of the events. This information can be utilized with any learning algorithm of choice, such as support vector machines (SVM) or decision forests (RF). The project is available at https://gitlab.com/danieleon1/TagEQ.

Data Flow for the TagEQ-CN System

The system operates using a configuration file, which serves as a guide for the system to locate the signal data, specify parameters for the classification algorithms, define label assignment parameters, determine the type of classification to be performed, and establish rules for label application. Figure 1 illustrates the data flow and system architecture.

Figure 1. Data flow and system architecture



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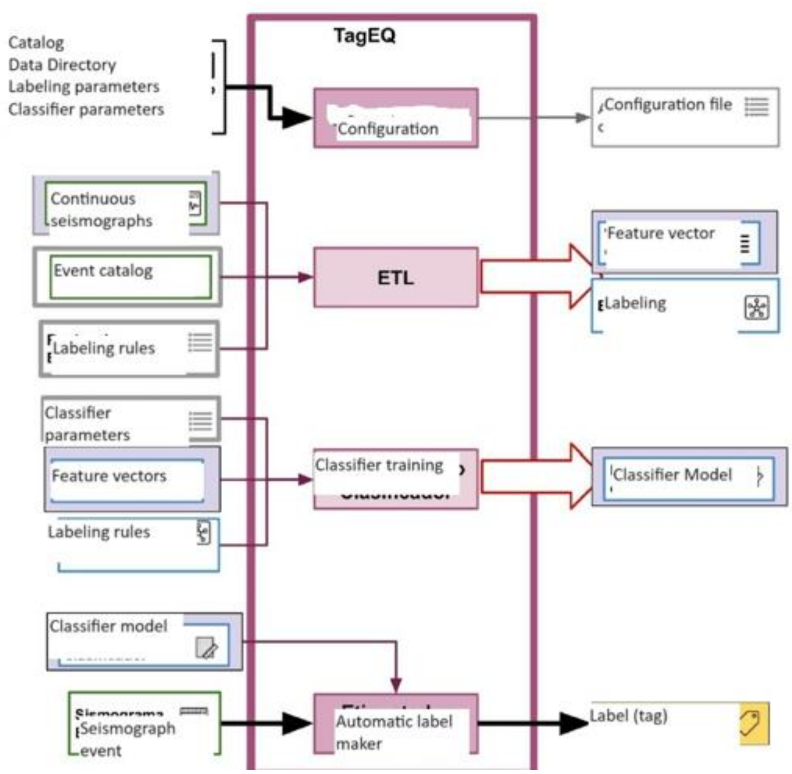
The tasks in Figure 1 involve:

- Executing preprocessing steps for continuous seismograms, extracting signals corresponding to events listed in the catalog, and defining rules for assigning labels to these events.
- Creation of feature vectors based on event seismograms.
- Establishment of classifier models based on vectors and rules defined to label events.
- After the models are built, the label corresponding to each event is assigned by reading the seismogram of that particular event.

TagEQ-CN System Modules

Figure 2 illustrates the main system modules. Inputs, outputs, and the modular structure of the TagEQ-CN system are presented. This shows the four main modules: Configuration, ETL, Classifier training, and Automatic labeling. Each module operates automatically upon user prompting; however, only the Configuration and Automatic labeling modules require interaction for the user to deliver their respective output. Each system module is described in a detailed manner below.

Figure 2. TagEQ-CN system modules



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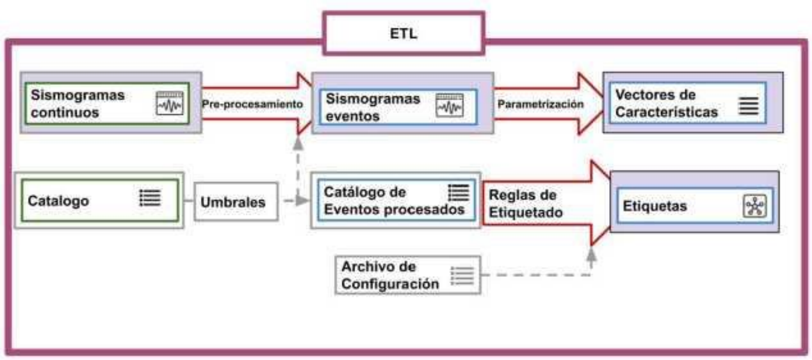
Configuration module: The aim of this module is for the user to explicitly state the directives with which they want the system to classify the signals. The system encompasses two types of directives: general and machine learning directives. The general directives outline the locations of the seismograms, the catalog utilized, the storage locations for generated data (event seismograms and annotated catalogs), and the rules employed for annotating the data. Machine learning directives specify the type of classifier and the parameters that are applied to tune these classifiers.

Extraction, transformation, and Loading (ETL) module: It executes all data preprocessing procedures and parameterizes the seismograms corresponding to events. Figure 3 illustrates the module's general operating scheme. The ETL module processes the inputs (which include continuous seismograms and a seismicity catalog) and produces the feature vectors necessary for event classification. By utilizing the source times provided in the seismicity catalog, the continuous seismograms are scanned for signals associated with the events. Subsequently, these signals are parameterized using various techniques and the resulting feature vectors are stored. For the architecture proposed in the TagEQ system, programs were developed to generate vectors based on the following criteria:

Figure 3. Extraction, transformation, and loading module



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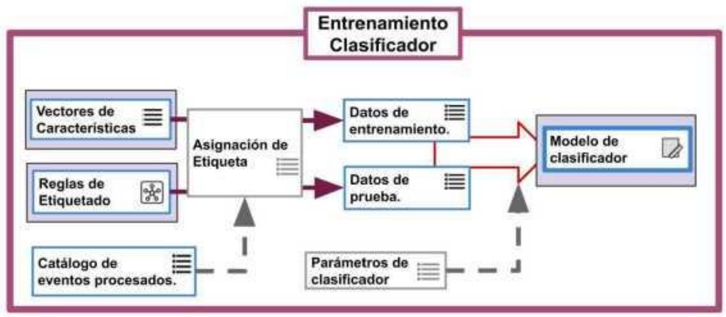
- *Statistics:* Average, variance, statistical skewness, and kurtosis are computed within 50-s windows for each of the three channels of the seismogram.
- *Sonogram:* It calculates the averages in 50-s lapses of the energy of nine frequency bands, with a basis on the algorithm proposed by [23].
- *Fractal dimension of the signal:* It calculates the fractal dimension of the vertical component within a specified window.
- *Fractal dimension variation:* It computes the variance of the fractal dimension calculated across different windows.
- *Covariance:* It computes the covariance matrix, rectilinearity, and planarity of the signal within a specified window.

Classifier training module: For classifier training, feature vectors are extracted and matched with corresponding labels. This assignment is accomplished by referencing the information within the catalog of processed events and determining the label based on the rules specified for the seismic network. Subsequently, the data is labeled by resolving the directive using the seismicity catalog. The information flow diagram for this module is illustrated in Figure 4.

Figure 4. Classifier training module



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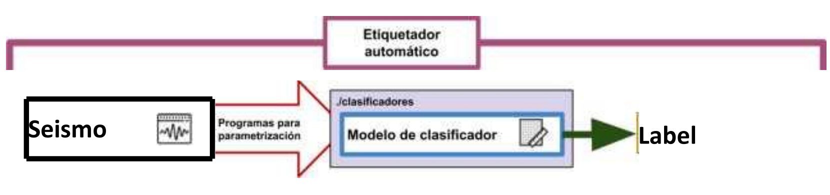
To construct the classifier model, a portion of the dataset is allocated for training purposes and the remaining segment is reserved for testing. For each classification algorithm, the parameters specified in the configuration file are utilized to either generate a single model or produce multiple models, from which the best-performing one is selected. For the TagEQ-CN system, the LibSVM libraries were employed for the SVMs [24] and the Ranger program was utilized for random decision forests [25, 26, 27].

Event labeling module: In this module, the system requires manual identification of the seismogram corresponding to the event slated for classification. Subsequently, the seismogram is parameterized, a feature vector is constructed, and then it is fed into the previously established model. Prediction using the trained classifier yields the event label. Figure 5 presents the schematic diagram of the operation of the labeling module.

Figure 5. Event labeling module



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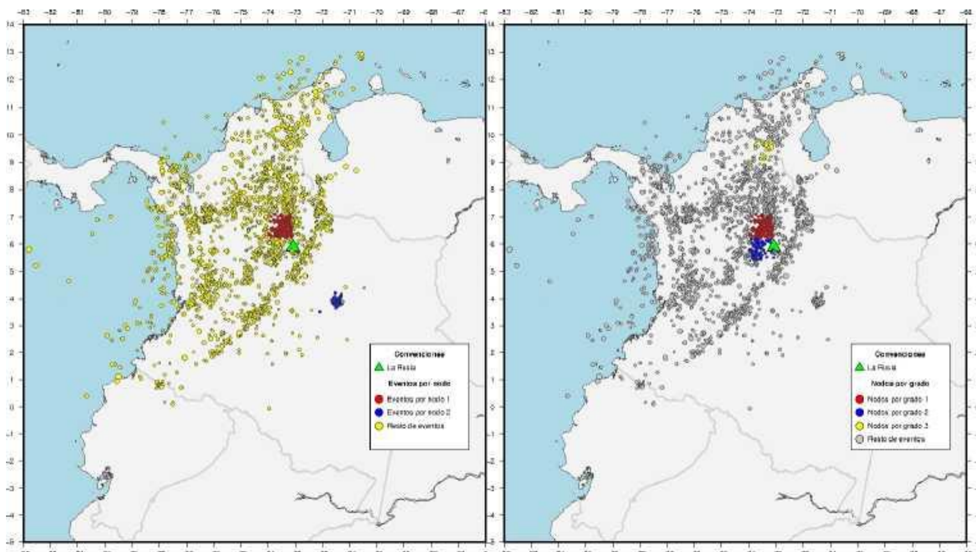
Results

The catalog used in this study comprises 51,520 events. Out of these events, only those with a magnitude greater than M > 2 and with sufficient seismic energy recorded at the La Rusia station were considered. In some instances, tests were conducted with events having a magnitude greater than M > 3. The final test set comprises 8,151 events with a magnitude greater than M > 2 and 502 events for M > 3. Algorithms were tested to conduct classification in scenarios based on event community membership, node degree, centrality, and number of events per node.

Figure 6 depicts the events labeled based on the number of events per node and the degree of the node. For the number of events, the events belonging to the two cells with the highest numbers were labeled and a third class was utilized to label the remaining events. In the case of event degree, the events associated with the three nodes with the highest degrees were labeled and a fourth class was designated to label the remaining events.

Figure 6. Event classification maps by membership in nodes with the highest number of events (Left) and by degree (right)



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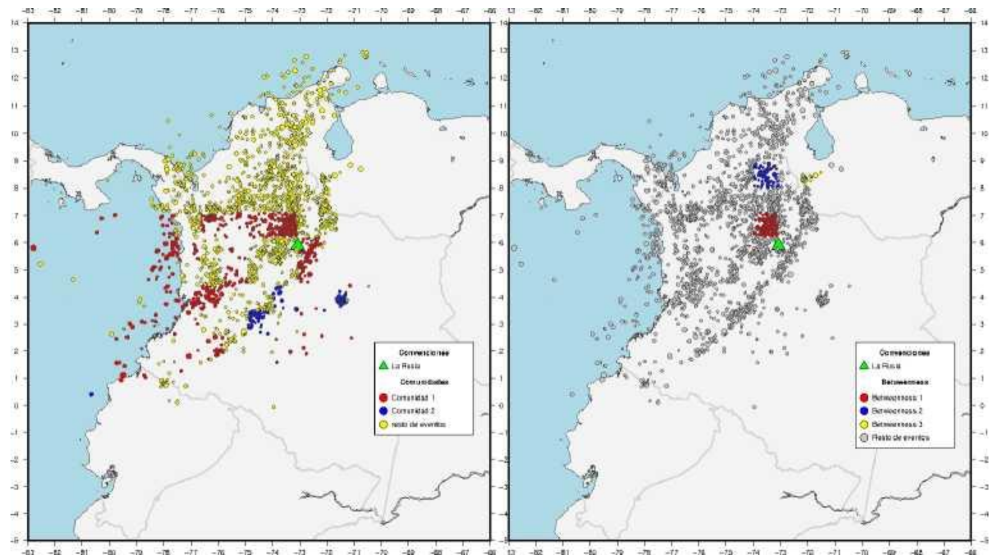
It is noteworthy to mention that the labeling conducted in both cases underscores the significance of the events transpiring in the Bucaramanga nest. It is also evident that in eastern Colombia, there exists a small region where numerous events converge within a single node. Regarding the degree of the cells, it is apparent that the cells near Bucaramanga exhibit extensive connections with other events as well as the events occurring further north between the departments of Cesar and Norte de Santander, along the border with Venezuela.

Figure 7 illustrates the labeling of events belonging to the two communities with the highest number of nodes, along with a third class for the remaining events (left). Moreover, the figure illustrates the labeling of events associated with the three nodes possessing the highest centrality index in the earthquake network, supplemented by a fourth class for the remaining events (right).

Figure 7. Event classification maps by node membership of the largest event communities (left) and the most central nodes of the earthquake network (right)

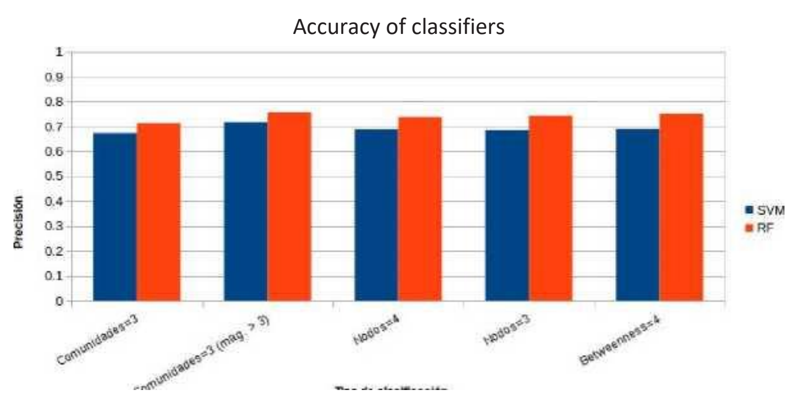


Source: Prepared by the authors

Figure 7 demonstrates that the abstraction level required to differentiate events of diverse categories is high. In the case of communities (Figure 7 left), it is apparent that members of the same category, such as red, are dispersed across different locations and often situated close to members of other categories. This poses a challenge for a single station attempting to differentiate all events. The same thing occurs with the other community.

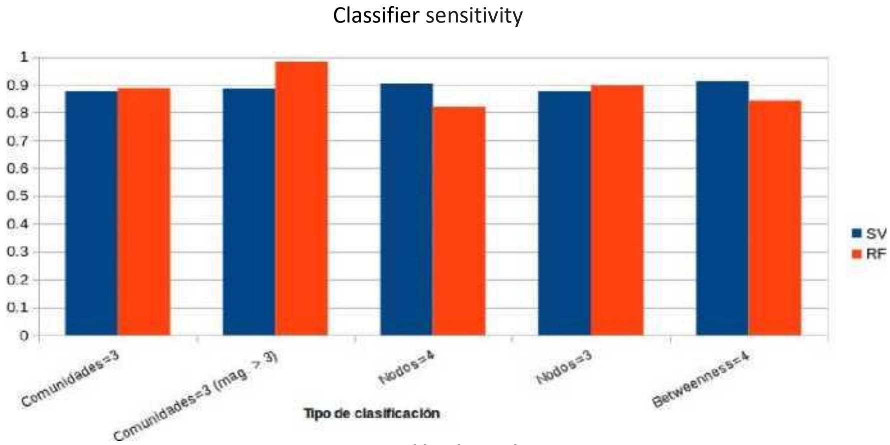
Using the annotation schemes depicted in Figures 6 and 7, SVM and random forest (RF) classifiers were trained. This involved randomly selecting 80% of the annotated event set for training and reserving 20% as the test set. The accuracies and sensitivities depicted in Figures 8 and 9 were obtained using the best SVM classifier with varying parameters, along with an RF classifier comprising 500 trees.

Figure 8. Accuracy of classifiers using SVMs and RFs



Source: Prepared by the authors

Figure 9. Sensitivity of classifiers using SVMs and RFs



Source: Prepared by the authors

From Figures 8 and 9, it is evident that the performance of RF is superior compared to SVM. The same conclusion was reached in [26], which compared the performances of SVM, RF, and a Bayesian classifier. This, combined with its faster training speed and ease of use, renders RF superior in performance compared to SVM. Nevertheless, it is worth noting that both classifiers exhibit only a minor difference in accuracy, suggesting that either of them could be utilized effectively. This indicates that the parameterization of the waveforms contains sufficient information to construct a robust classifier, even with limited training data (up to 8,151 events discriminated with magnitude M > 2). Out of the 51,520 events, smaller events were not examined because their energy levels are minimal, and they would only be detectable at this station if they were to occur in very close proximity.

Lastly, it is noteworthy that accuracy and sensitivity levels consistently remain above 70%, with only SVM hovering very close to this threshold. The sensitivity in this multiclass scenario pertains to the number of items from one category that are correctly labeled as belonging to another category. The high percentage indicates that few items are mislabeled in this context.

Conclusions

The developed system operates within the supervised paradigm, albeit with a considerable degree of automation. Users are not directly involved in selecting the signal sets for training and testing the classifier nor do they assign labels to the events. Instead, labels are assigned based on a pre-existing catalog of earthquakes originating from an initial annotation conducted by an analyst. In addition, high-level rules defined by the user play a role in the labeling process. Given the level of abstraction attained by the classifier, it is conceivable that it could also be applied to other types of signals, such as those from landslides, explosions, or fluid movement. However, to employ this technique, it is necessary to create a catalog of event times and to establish some form of signal identification.

Classifying seismic events with a single station can be immensely beneficial in situations where a large sensor network is unavailable. Utilizing a single station for event classification could assist an analyst in generating an alarm to investigate a situation based on a single acquired signal, eliminating the need to wait for signals from other stations. This eventually provides a preliminary report that alerts a seismological data operator with more comprehensive preliminary information rather than merely indicating that a signal surpassed an energy threshold.

The developed system exhibits a high degree of modularity, enabling the incorporation of new features into the feature vectors through the creation of additional programs capable of extracting analyzed information from a seismogram.

The accurate results suggest that the selected parameters for representing the events in the feature vectors are adequate. However, to enhance the level of abstraction with events comprising diverse components and waveforms, additional features may be necessary.

It was observed that RF and SVM classifiers performed well. The findings also suggest that RF is better suited for classifying seismic signals.

By leveraging the high-level rules established within the catalog, analysts can swiftly pinpoint potential signals of interest (whether they are categorized as deep or shallow events, large or small, or belonging or not belonging to a specific category). This can be achieved through the integration of a detection algorithm alongside a classification algorithm.

For future development, considering the current status as a prototype classifier, there is a proposal to enhance user experience by creating a user-friendly interface and to establish a comprehensive framework enabling the definition of high-level directives for label assignment purposes.

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