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Can artificial intelligence help detect nuclear explosions?

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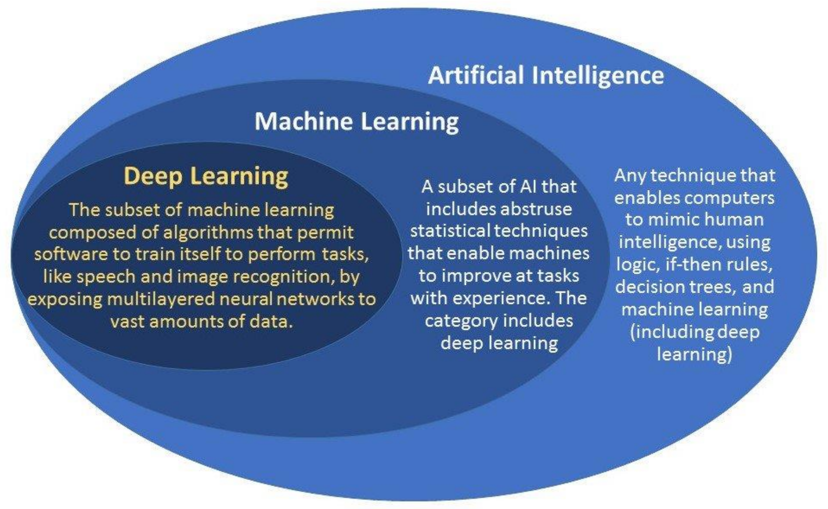
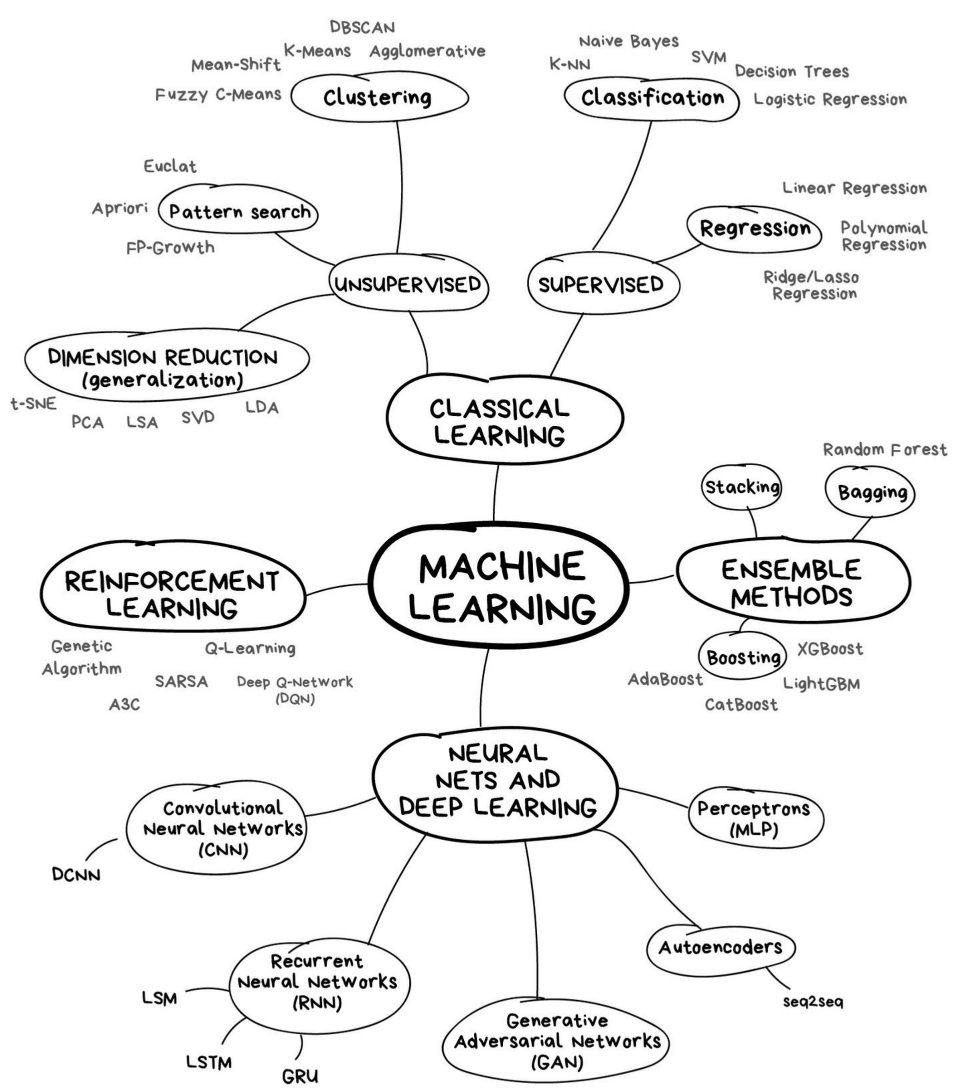
Abstract

The field of artificial intelligence has had an exponential growth in its application in recent years. In particular, machine learning is an effective tool to solve problems that seek to find patterns of behavior from large databases. This boom was largely due to the new and increasingly powerful computing capabilities and a large amount of data available. The IMS has 306 stations installed, 6 under construction and 25 planned. This represents a large volume of data that is published daily. The application of machine learning can improve the search of patterns in this data to optimize the processing, and the automatic response to a possible nuclear explosion. A review of the applications of machine learning techniques for improving the processing of data from different types of IMS stations is presented.

Introduction





https://vas3k.com/blog/machine_learning/

The IMS foresees a network of 321 geophysical monitoring stations, with the majority of these being seismic stations (170); followed by radionuclide detectors for particulates and noble gases (80); infrasound arrays (60); and hydroacoustic sensors (11)

In full operation, around 15 gigabytes of incoming data are expected daily, mostly transmitted in real time through a global VSAT satellite network. This amount of incoming data makes reliable automatic processing and is one of many factors fostering the exploration of adaptive signal processing and machine learning solutions for IMS data processing.

Disclaimer: The views expressed on this poster are those of the author and do not necessarily reflect the view of the CTBTO

Applications

Seismic Stations

Seismic monitoring stations measure the waves generated by seismic events. These events can be of natural origin, man-made or underground nuclear explosion. Different strategies have been studied to automatically classify these events using machine learning.

NET-VISA [1] is a Bayesian seismic monitoring system, based on the use of generative probabilistic models and allows to reduce in about 60% the number of events lost compared with the system currently implemented.

The number of seismological studies based on Artificial Neural Networks (ANN) has been increasing. The ANN are very useful in the analysis of time series as are measurements of seismographs. The implementation of Deep Neural Networks (DNN) for the analysis of seismic data present the following advantages [2]:

- Unlabeled data can be used to pretrain the DNN (unsupervised learning);
- Learning how to solve a particular problem requires a small amount of labeled data (supervised learning);
- Higher learning speed and fewer errors during operation;
- They are simple to retrain to solve other Tasks

However, large volume of data is required for training.

A different method has been presented by [3]. This involves the use of Principal Component Analysis (PCA) and Self-Organized Maps (SOM). This method of clustering by unsupervised pattern recognition can be summarized in three steps:

1. Short-time Fourier transform (STFT) is applied obtaining the sonogram that consist in the Power spectral density
2. PCA is performed on the training dataset and the sonograms of the training events are transformed in the space of the first principal components.
3. The SOM is trained on the PCA-reduced sonograms of the training dataset.

The accuracy obtained with this model is greater than 80%.

Infrasound Stations

Infrasonic sensors measure micropressure changes in the atmosphere which are generated by the propagation of infrasonic waves. These very low frequency waves can also be created by atmospheric nuclear explosions.

Several studies show the use of DNN in the analysis of infrasound signals. In [4] the implementation of the DNN standard model, self-normalizing neural network (SNN), fully-convolutional neural network (FCN), and a long short-term memory (LSTM) network is shown. All the models used have been able to classify almost perfectly the four classes of infrasonic events, including mountain associated waves, microbaroms, auroral infrasonic waves, and volcanic eruptions.

Although the DNN are very effective for classifying infrasonic events these fail when the volume of data available is low. This problem can be solved using the model Shepard Interpolation Neural Networks (SINN) [5]. With this model, high levels of accuracy are achieved with little data for training.

Radionuclide Stations

The radionuclide monitoring stations measure the concentration of radioactive particles and noble gases. Radionuclides can occur naturally or artificially (Nuclear power plants, MIPFs, etc). Four xenon isotopes (^{135}Xe, ^{133}Xe, ^{133m}Xe, ^{131m}Xe) are particularly relevant for the detection of nuclear explosions.

The main difficulty encountered in applying Machine Learning algorithms is that the dataset with which they are counted are strongly unbalanced. That is, the background class is preponderant against the explosion class.

Two different perspectives of the classification problem of noble gas measurements are:

In [6] a classic vision for solving the problem of classification is proposed:

- The data set used is composed of:
  - A background dataset (B) obteined by real measurement of the SPALAX station located in Ottawa for the following dates: June 1,2004 – June 30, 2005
  - A background plus synthetic explosion data set (B+E). The synthetisized data is produced by using real data from measuremnts from the Nevada Test Site
- The implemented algorithms are: Naïve Bayes (NB), Multiple Layer Perceptron (MLP), Support Vector Machine (SVM), k-Nearest Neighbors (kNN), and Decision Tree (DT).
- The accuracy reported for each classifier ranges between 83% and 98.9%

In [7] using pattern recognition of One-Class models is proposed:

- The dataset was synthesized using the framework presented in [8].
- The simulation of the data set includes an industrial emmiter.
- The atmospheric conditions such as the fluctuation of the wind speed and its direction are taken into account to calculate the background level.
- They have studied the performance of their models depending on the distance from the explosion to the monitoring station.
- The implemented algorithms are: The autoassociator (AA), Combined Probability and Density Estimator (PDEN), one-class Nearest Neighbour (ocNN) algorithm, scaled ocNN (socNN, a modified version of the ocNN).
- The mean AUC reported for each classifier ranges between 0.5 and 0.6. However, when wind patterns are considered, the mean AUC improves.

Conclusion

- The Machine Learning and Deep Learning use for the automatic processing of the IMS stations signals is very useful for events classification.
- The imbalance that exists in the training dataset is a great challenge to solve.
- It is necessary to expand access to datasets so that a larger scientific community can get involved in these problems.
- It would be convenient to increase the diffusion of the vDEC for a better civil use of the data.
- A methodology for the anonymity of data should be established to facilitate the distribution of it.
- Although these techniques of Machine Learning and Deep Learning show a great precision in the classification of events, we can not presume from the human analysis of the data.

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