Journal of African Earth Sciences 128 (2017) 116–126

Contents lists available at ScienceDirect

Journal of African Earth Sciences

journal homepage: www.elsevier.com/locate/jafrearsci

Application of support vector machines for copper potential mapping in Kerman region, Iran

Mahdi Shabankareh, Ardeshir Hezarkhani*

Mining and Metallurgical Department, AmirKabir University of Technology, Tehran, Iran

ARTICLE INFO

Article history:
Received 25 April 2016
Received in revised form
29 October 2016
Accepted 10 November 2016
Available online 20 December 2016

Keywords:
Copper prospecting
Potential mapping
Support vector machines
Evidential layers analysis
Exploration characteristics

ABSTRACT

The first step in systematic exploration studies is mineral potential mapping, which involves classification of the study area to favorable and unfavorable parts. Support vector machines (SVM) are designed for supervised classification based on statistical learning theory. This method named support vector classification (SVC). This paper describes SVC model, which combine exploration data in the regional-scale for copper potential mapping in Kerman copper bearing belt in south of Iran. Data layers or evidential maps were in six datasets namely lithology, tectonic, airborne geophysics, ferric alteration, hydroxide alteration and geochemistry. The SVC modeling result selected 2220 pixels as favorable zones, approximately 25 percent of the study area. Besides, 66 out of 86 copper indices, approximately 78.6% of all, were located in favorable zones. Other main goal of this study was to determine how each input affects favorable output. For this purpose, the histogram of each normalized input data to its favorable output was drawn. The histograms of each input dataset for favorable output showed that each information layer had a certain pattern. These patterns of SVC results could be considered as regional copper exploration characteristics.

1. Introduction

The first step in systematic exploration studies is mineral potential mapping (MPM). Mineral exploration is a multidisciplinary task requiring the simultaneous consideration of numerous disparate geophysical, geological, and geochemical datasets (Moon et al., 2006). Additionally, the variety of sources such as remote sensing, airborne geophysics, and large commercially available geological and geochemical data are increasing the size and complexity of regional exploration data (Asadi et al., 2016; Brown et al., 2000; Ford et al., 2016; McKay and Harris, 2016). These sorts of data can be visualized, processed and analyzed with the support of computer and GIS techniques (Bonham-Carter, 1994; Carranza, 2008; Pan and Harris, 2000). Thus, MPM is a multiple criteria decision-making (MCDM) task and produces a predictive model for outlining prospective areas (Abedi et al., 2012; Yousefi and Carranza, 2015a).

Earth science information used in MPM has an empirical component comprising an exploration database and a conceptual component comprising an expert knowledge-base. Actually, these components was used for the classification of a study area to favorable and unfavorable parts. The favorable parts are suggested for further exploration. There are two types of classification techniques. One type is known as supervised classification, which classifies mineral prospectivity of every location based on a training set of locations of known deposits and non-deposits and a set of evidential data layers (Gonbadi et al., 2015). The other type is known as unsupervised classification, which classifies mineral prospectivity of every location based solely on feature statistics of individual evidential data layers (Zuo and Carranza, 2011).

Every geocomputational technique has advantages and disadvantages, and one or the other may be more appropriate for a given geologic environment and exploration scenario (Carranza, 2011). Some of the geocomputational modeling techniques have been proposed for mineral potential mapping, are weights of evidence (Agterberg et al., 1990; Agterberg and Bonham-Carter, 2005; Benomar et al., 2009; Bonham-Carter et al., 1988, 1989; Carranza and Hale, 2000; Carranza, 2004; Harris et al., 2008; Jianping et al., 2005; Nykänen and Ojala, 2007; Nykänen and Raines, 2006; Oh and Lee, 2008; Pan, 1996; Porwal et al., 2006; Raines, 1999; Raines et al., 2007; Rencz et al., 1994; Roy et al., 2006; Tangestani and Moore, 2001; Xu et al., 1992), bayesian network classifiers (Porwal et al.,

* Corresponding author. Department of Mining and Metallurgical, AmirKabir University of Technology, 424 Hafez Ave, P.O. Box 15875-4413, Tehran, Iran.
E-mail address: ardehez@aut.ac.ir (A. Hezarkhani).

http://dx.doi.org/10.1016/j.jafrearsci.2016.11.032
1464-343X/

2006), logistic regression (Agterberg, 1988; Chung and Agterberg, 1980; Carranza and Hale, 2001a; Oh and Lee, 2008), fuzzy logic (An et al., 1991; Bonham-Carter, 1994; Carranza and Hale, 2001b; Carranza et al., 2008a; D'Ercole et al., 2000; De Quadros et al., 2006; Eddy et al., 1995; Elliott et al., 2016; Knox-Robinson, 2000; Luo and Dimitrakopoulos, 2003; Nykänen et al., 2008; Yousefi and Carranza, 2015b), artificial neural networks (Behnia, 2007; Brown et al., 2000, 2003; Harris and Pan, 1999; Oh and Lee, 2008; Porwal et al., 2003, 2004; Rigol-Sanchez et al., 2003; Singer and Kouda, 1996; Skabar, 2007), evidence theory model (An and Moon, 1993; Carranza et al., 2005; Carranza and Hale, 2003; Carranza, 2015; Moon, 1990, 1993; Moon and So, 1995).

Actually, if there are databases from previous exploration projects or mining activities, MPM can classify study area to favorable and unfavorable parts for further exploration activities with supervised and unsupervised classifications.

Support vector machines (SVMs) as an empirical method (a data-driven technique) are supervised learning algorithms, which are considered as heuristic algorithms, based on statistical learning theory (Vapnik, 1995). This method was further developed in various supervised classification applications during the last decade. Examples of the use of the SVM are available in studies of various issues. This method, also, was used in MPM (Abedi et al., 2012; Geranian et al., 2016; Rodriguez-Galianoa et al., 2015; Zuo and Carranza, 2011).

MPM by using SVM studies were focused on modeling and evaluation of the model. These studies didn't ponder on the effect of evidential layers on modeling output.

This paper describes SVM model, which combine exploration data in the regional-scale for copper potential mapping in Kerman copper bearing belt in south of Iran. Finally, the effect of each input parameter on output result (final map) will be discussed. The effects of the input parameters and their interpretation help to finding exploration criteria of copper mineralization in the study area.

2. Method: support vector machine model

The original SVM algorithm was proposed by Vapnik (1995), and provided a powerful tool for pattern recognition (Burges, 1998; Lu et al., 2001) to deal with problems that had nonlinear, large and limited data samples. An important feature of the SVM as a supervised learning algorithm is the determination of the model parameters corresponds to a convex optimization problem, and therefore any local solution is also a global optimum (Bishop, 2006).

The support vectors utilize a hyperplane with maximum margin to separate different classes of data producing a satisfactory overall performance. Thus, this methodology can provide a single solution with a strong regularized feature that is very suitable for classification problems that are poorly conditioned. The SVM technique has been used for various applications such as face recognition, time series forecasting (Ahn et al., 2011), fault detection (Gryllias and Antoniadis, 2012; Park et al., 2011) and modeling of nonlinear dynamical systems (Gonbadi et al., 2015; Wu, 2011).

To describe the method, we must first discuss the issue in terms of the two-class problem. Suppose there is a training set of data vectors composed of l feature vectors $x_i \in R^n$, where i (=1, 2, …, n) is the number of samples. The class to which a sample is assigned is labeled y_i, which is equal to 1 for one class or −1 for the other class (i.e.$y_i \in \{-1, 1\}$) (Huang et al., 2002). If the two classes are linearly separable, then there exists a group of linear separators called separating hyperplanes that satisfy the following set of equations (Kavzoglu and Colkesen, 2009) (Fig. 1).

$$wx_i + b \geq +1 \quad for \quad y_i = +1$$

$$wx_i + b \leq -1 \quad for \quad y_i = -1$$

which is equivalent to

$$y_i(wx_i + b) \geq 1, \quad i = 1, 2, \ \ldots, \ n$$

The separating hyperplane can then be formalized as a decision function

$$f(x) = sgn(wx + b)$$

where, sgn(x) is a sign function, which is defined as follows:

$$sgn(x) = \begin{cases} 1, & if\ x > 0 \\ 0, & if\ x = 0 \\ -1, & if\ x < 0 \end{cases}$$

The two parameters of the separating hyperplane decision function, w and b, can be obtained by solving the following optimization function:

$$Minimize\ \tau(w) = \frac{1}{2}\left\|w^2\right\|$$

subject to

$$y_i((wx_i) + b) \geq 1, \ i = 1, \ \ldots, \ l$$

The solution to this optimization problem is the saddle point of the Lagrange function

$$L(w, b, \alpha) = \frac{1}{2}\left\|w^2\right\| - \sum_{i=1}^{l} \alpha_i (y_i((x_i w) + b) - 1$$

$$\frac{\partial}{\partial b} L(w, b, \alpha) = 0 \quad , \quad \frac{\partial}{\partial w} L(w, b, \alpha) = 0$$

where α_i is a Lagrange multiplier. The Lagrange function is minimized with respect to w and b and is maximized with respect to $\alpha_i > 0$. Lagrange multipliers α_i are determined by the following optimization function:

$$Maximize \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{ij=1}^{l} \alpha_i \alpha_j y_i y_j (x_i x_j)$$

subject to

$$\alpha_i \geq 0, \quad i = 1, \ \ldots, \ l, \ and \sum_{i=1}^{l} \alpha_i y_i = 0$$

The separating rule, based on the optimal hyperplane, is the following decision function:

$$f(x) = sgn\left(\sum_{i=1}^{l} y_i \alpha_i (x x_i) + b\right)$$

More details about SVM algorithms can be found in Vapnik (1995) and Tax and Duin (1999).

In machine learning, support vector machines for classification (SVC) are supervised learning models with associated learning algorithms that analyze data and recognize patterns. The basic SVM takes a set of input data and predicts, for each given input, which of two possible classes form the output, making it a non-probabilistic