Chapter 7
A Classification Model Based on Improved Self-Adaptive Fireworks Algorithm

Yu Xue
Nanjing University of Information Science and Technology, China

ABSTRACT

As a recently developed swarm intelligence algorithm, fireworks algorithm (FWA) is an optimization algorithm with good convergence and extensible properties. Moreover, it is usually able to find the global solutions. The advantages of FWA are both optimization accuracy and convergence speed which endue the FWA with a promising prospect of application and extension. This chapter mainly focuses on the application of FWA in classification problems and the improvement of FWA. Many prior studies around FWA have been produced. The author here probes improvement of FWA and its application in classification. The chapter studies FWA around: (1) Application of FWA in classification problems; (2) Improvement of FWA's candidate solution generation strategy (CSGS), including the employment of self-adaptive mechanisms; (3) Improved SaFWA and classification model. For each part, the author conducts research through theory, experimentation, and results analysis.

THE APPLICATION OF FWA IN CLASSIFICATION PROBLEMS

Classification Problems

Classification problems have been researched for several decades. The purpose of classification is to correctly predict the classification labels of unseen instances according to the characteristics of these instances. This issue is divided into two categories, i.e., unsupervised clustering and supervised classification. Clustering is an important research topic and it has been applied in many fields (Yu Xue, Zhao, & Ma, 2016). The main methods for solving clustering problems including K-means (Zhao, Chen, & Chen, 2017), Fuzzy c-means (FCM) (Manimala, David, & Selvi, 2015) and evolutionary computation (Y. Xue, Zhuang, Meng, & Zhang) (EC). K-means and FCM have been widely researched. However,

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both K- means and FCM are sensitive to the initial clustering centers. Thus, the solutions of K-means or FCM algorithms often easily fall into local optima. Furthermore, the parameter value of clustering centers should be given in advance. Therefore, EC techniques, which can solve the optimization problems without much information, are employed to overcome these defects in clustering methods and the evolutionary clustering methods have better performance for solving the clustering problems.

Classification methods, such as support vector machine (SVM) (Martins, Costa, Frizera, Ceres, & Santos, 2014), artificial neural network (ANN) (Oong & Isa, 2011), k-nearest neighbor (KNN) (Peterson, 2009) have become hot research topics in the past several decades. However, most of them are deterministic, they might easily be trapped into local optima. Different from the situation in clustering research field, EC techniques have been only used to improve the accuracy of the classifiers either by optimizing their parameters and structures, or by pre-processing their inputs.

As a recently developed swarm intelligence algorithm, Fireworks Algorithm (FWA) (Ying & Zhu, 2010) is an optimization algorithm with good convergence and extensible properties. Moreover, it is usually able to find the global solutions. The advantages of FWA are both optimization accuracy and convergence speed which endue the FWA with a promising prospect of application and extension. It has been proven that FWA is efficient in dealing with optimization problems. The purpose of this chapter is to investigate the feasibility of solving classification problems by EC techniques through an evolutionary optimization classification model and investigate the performance of FWA when it is employed to solve the classification problems (Yu, Binping, Tinghuai, & X., 2018). We firstly convert the classification problem into an optimization problem, then employ the FWA to solve the optimization problem. Moreover, Particle Swarm Optimization (PSO) (Tanweer, Suresh, & Sundararajan, 2015) is used as a comparison algorithm. Because PSO is a commonly used algorithm.

Evolutionary Optimization Classification Model

Give a dataset $D = \{x_1, x_2, \ldots, x_m\}$ and a training set $T = \{(x_1, y_1), \ldots, (x_m, y_m)\}$, where (x_i, y_i) is the i^{th} example, $x_i = x_{i1}, x_{i2}, \ldots, x_{id} \in X = R^d$ is the i^{th} sample, $y_i \in Y = \{1,2,\ldots,l\}(1,2,\ldots,m)$ is the label of the i^{th} sample. The task of classification problem is to learn a model $f(x)$: $X \rightarrow Y$ from the training set T.

The examples of a training dataset can be written as:

$$\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1d} & y_1 \\ x_{21} & x_{22} & \cdots & x_{2d} & y_2 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{md} & y_m \end{bmatrix} \tag{1}$$

First, we introduce a weight vector $W = (w_1, w_2, \ldots, w_d)$ and let:

$$\begin{cases} w_1 x_{11} + w_2 x_{12} + \ldots + w_d x_{1d} = y_1 \\ w_1 x_{21} + w_2 x_{22} + \ldots + w_d x_{2d} = y_2 \\ \ldots + \ldots + \ldots + \ldots = \ldots \\ w_1 x_{m1} + w_2 x_{m2} + \ldots + w_d x_{md} = y_m \end{cases} \tag{2}$$