A SHORT NOTE ON THE OPPORTUNITY OF USING THE ADABOOST ALGORITHM IN ELECTRICAL POWER SYSTEMS

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Tehnica Boosting s-a dovedit a fi foarte utilă în domeniul învățării automate, având diferite aplicații practice. Cu toate acestea, în domeniul electric nu a fost folosită până în prezent, fiind citate doar două studii pe această temă. Lucrarea de față reprezintă o notă pe tema utilizării învățării automate cu Boosting pe o scară mai largă în cadrul rețelelor electrice, ținând seama de avantajele unei astfel de abordări.

Boosting proved its capabilities in enhancing machine learning routines and have been successfully applied in several real-life applications. However, only two applications in power systems studies have been reported so far. This short note paper shows the possibility of using Boosting on larger scale in power systems applications.

Keywords: boosting, machine learning, data analysis, electric networks

1. Introduction

The evolution of power grids towards "smarter" ones is bringing after itself an increase in their complexity, both from the operational point of view and regarding the way they are managed.

New Intelligent Electronic Devices (IEDs) are being installed on expanding scales. Technological advances enable these IEDs to acquire and transmit very large amounts of data. However, data from IEDs have to be processed and analyzed quickly, so that human operators or automated self-healing structures can make decisions and act in due time.

The decision making processes in power systems can employ several types of aggregated data, from topology analysis, bad data rejection and alarm processing to system operation state identification, most of these applications relying on classification tasks.

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Applications concerning data processing in power systems have been approached so far by means of artificial intelligence techniques, like expert systems and neural networks [1] and more recently, rough sets [2].

A simple system state classification problem is presented in the following. The states of the monitored system change over time, so data collected on-line have to be assessed in a suitable manner. Moreover, power system data consists of both analog (eg. voltages, currents, power flows) and digital signals (eg. status of circuit breakers, flags coding the operation of relays). But decision making is not done based on data. Data has to be transformed subsequently into information and then into knowledge, in a timely manner. Therefore, instruments that use data as inputs and transform it internally into information, output only aggregated state reports that help operators understand the current situation of the network.

The classification of the system state can be done either into two classes (safe/unsafe) or into multiple classes (for example, normal, alert, emergency and safe). [3]

Whatever the case, the classification technique has to process and summarize, and most importantly, to identify key information about the system operating conditions.

This approach would lead to a relief of the human operator, who would no longer have to cope with large amounts of data, some of which inconsistent, or with avalanches of alarms.

This paper proposes a new approach in power system classification tasks, based on machine learning with Boosting. Section 2 gives an outline of the Boosting method and section 3 presents a short exemplification. Section 4 contains some concluding remarks.

2. Machine learning and Boosting

The concept of Boosting supervised learning has its origins in a popular machine learning technique, *probably approximately correct* learning (PAC learning) [4] and it is based on the idea that a set of weak learners can be combined so as to generate a single strong learner. Boosting is a powerful learning concept; it provides a solution to the supervised classification learning tasks.

The first Boosting algorithm with provable polynomial time was proposed by Schapire [5]. Kearns and Vailant proved that learners performing only slightly better than random (weak learners that can classify examples better than random guessing) can be combined to form an ensemble hypothesis (or learner), provided there is sufficient data available [6]. The latter one is said to be a strong learner, i.e. it is arbitrarily correlated to the correct classification.

Let h_1, $h_{2, \dots,}$ h_n be a set of hypotheses. The composite hypothesis can be written as:

$$f(x) = \sum_{t=1}^{n} \alpha_t h_t \tag{1}$$

where α_i is the weighting coefficient of hypothesis h_i (learner) [5].

Both parameters from (1) have to be set by the Boosting procedure. The main variation between many boosting algorithms is their method of weighting training data points and hypotheses. Among these variations, the AdaBoost (Adaptive Boosting) is known as the first step of Boosting applications in real-world problems [7].

Some of these include power systems applications, but there is very little literature on the subject. As it seems, *only two* applications of Boosting in power systems have been proposed prior to this paper. The first was a non-intrusive technique for monitoring the power consumption of various household appliances [8]. The other concerns power system security assessment and uses AdaBoost [9].

The pseudocode of a generalized AdaBoost algorithm is given in Figure 1, as proposed by Schapire and Singer [10]. More detailed information about AdaBoost can be found in [11].

Given: $(x_1, y_1), \ldots, (x_m, y_m)$ where $x_i \in X$, $y_i \in Y = \{-1, +1\}$
Initialize $D_1(i) = 1/m$.
For $t = 1, \ldots, T$:

- Train base learner using distribution D_t.
- Get base classifier $h_t : X \to \mathbb{R}$.
- Choose $\alpha_t \in \mathbb{R}$.
- Update:

$$D_{t+1}(i) = \frac{D_t(i) \exp(-\alpha_t y_i h_t(x_i))}{Z_t}$$

where Z_t is a normalization factor (chosen so that D_{t+1} will be a distribution).

Output the final classifier:

$$H(x) = \operatorname{sign}\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right).$$

Fig. 1. The AdaBoost Algorithm

3. The possibility of using Boosting in power engineering

The previous section introduced some foundations of Boosting. The purpose of this section is to examine some of the properties of Boosting, particularly AdaBoost, in relation to power engineering applications.

For the simplicity of exposure, we shall refer to classification problems. As shown in section 1, the process of decision making in power systems frequently relies on classification tasks. The purpose of this note paper is not to provide a full solution to a given problem, but to prove the applicability of AdaBoost in power system applications.

As previously stated, the classification of power system states can be made, in the simplest form, into two classes. A very simple example is given in Table 1 (N- within normal values, H- higher than normal, L- lower than normal), with 6 attributes, corresponding to voltage, V, and current, I, measurements acquired from three IEDs. Figure 2 presents the results of AdaBoost for a classification problem, with 30 weak learners and a training set of 200 examples. As it can be observed, the two classes are linearly separable. However, classification problems from real-life power systems do not usually follow this restriction, but AdaBoost also performs very well for non-linearly separable spaces (figure 3).

Table 1

Example system states

IED1 V1 I1	IED2 V2 I2	IED3 V3 I3	State
N N	N N	N N	Safe
L H	N N	N H	Safe
L L	N L	H L	Unsafe
N H	N N	N N	Unsafe
L H	N L	L H	Unsafe

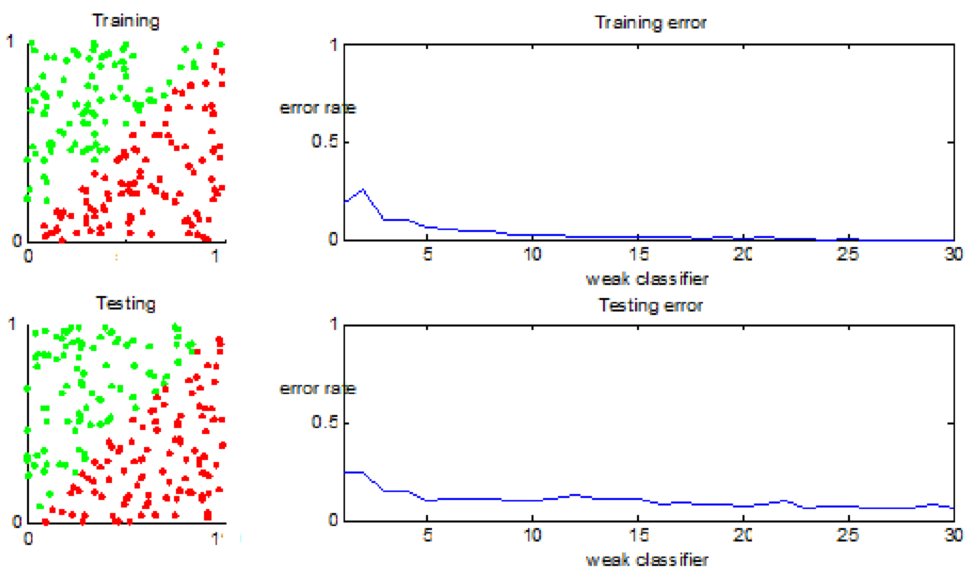

Fig. 2. AdaBoost performance for two linearly separable classes

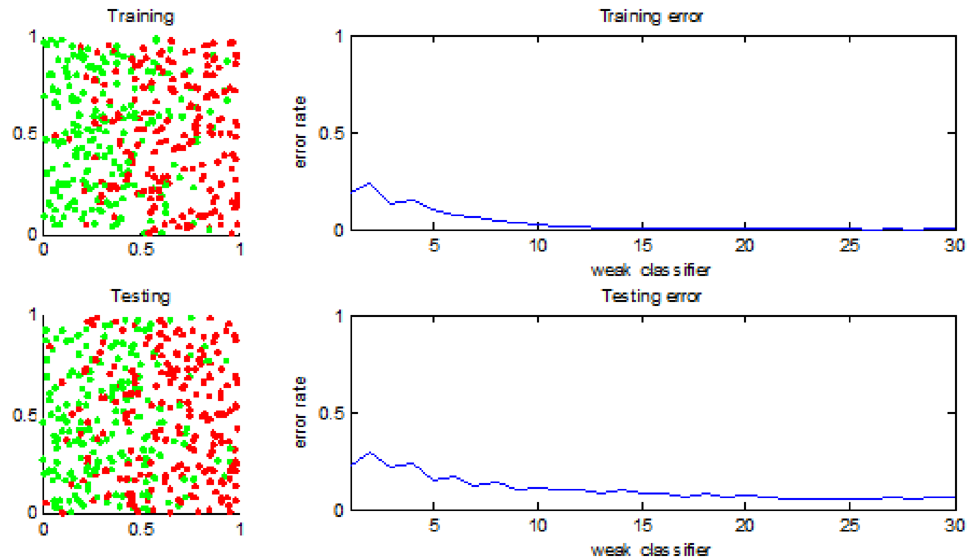

Fig. 3. AdaBoost performance for two non-linearly separable classes

These simple examples are only intended to show the capabilities of AdaBoost in correlation to power systems classification tasks. However, Boosting can handle more complex problems and multiple classes.

4. Conclusions

Machine learning techniques have been successfully applied in electrical power systems, and advances in theoretical studies should also move forward their power systems applications, as “intelligence” is needed in order to enable the full capabilities of electrical networks, as their operation implies large amounts of data.

This note paper briefly presented the capabilities of AdaBoost for classification tasks, related to power systems applications.

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