Change Detection with Kalman Filter and CUSUM

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Abstract. In most challenging applications learning algorithms acts in dynamic environments where the data is collected over time. A desirable property of these algorithms is the ability of incremental incorporating new data in the actual decision model. Several incremental learning algorithms have been proposed. However most of them make the assumption that the examples are drawn from a stationary distribution [13]. The aim of this study is to present a detection system (DSKC) for regression problems. The system is modular and works as a post-processor of a regressor. It is composed by a regression predictor, a Kalman filter and a Cumulative Sum of Recursive Residual (CUSUM) change detector. The system continuously monitors the error of the regression model. A significant increase of the error is interpreted as a change in the distribution that generates the examples over time. When a change is detected, the actual regression model is deleted and a new one is constructed. In this paper we tested DSKC with a set of three artificial experiments, and two real-world datasets: a Physiological dataset and a clinic dataset of Sleep Apnoea. Sleep Apnoea is a common disorder characterized by periods of breathing cessation (apnoea) and periods of reduced breathing (hypopnea) [7]. This is a real-application where the goal is to detect changes in the signals that monitor breathing. The experimental results showed that the system detected changes fast and with high probability. The results also showed that the system is robust to false alarms and can be applied with efficiency to problems where the information is available over time.

1 Introduction

In most challenging applications learning algorithms acts in dynamic environments where the data is collected over time. A desirable property of these algorithms is the ability of incremental incorporating new data in the actual decision model. Several incremental learning algorithms have been proposed to deal with this ability (e.g., [5, 12, 6]). However most learning algorithms, including the incremental ones, assume that the examples are drawn from a stationary distribution [13]. In this paper we study learning problems where the process

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generating data is not strictly stationary. In most of real world applications, the target concept could gradually change over time. The ability to incorporate this concept drift is a natural extension for incremental learning systems.

In many practical problems arising in quality control, signal processing, monitoring in industrial plants or biomedical, the target concept may change rapidly [2]. For this reason, it is essential to construct algorithms with the purpose of detecting changes in the target concept. If we can identify abrupt changes of target concept, we can re-learn the concept using only the relevant information. There are two types of approaches to this problem: methods where the learning algorithm includes the detection mechanism, and approaches where the detection mechanism is outside (working as a wrapper) of the learning algorithm. The second approach has the advantage of being independent of the learning algorithm used. There are also several methods for solving change detection problems: time windows, weighting examples according their utility or age, etc [9]. In the machine learning community few works address this problem. In [15] a method for structural break detection is presented. The method is an intensive-computing algorithm not applicable for our proposes of processing large datasets.

The work presented here follows a time-window approach. Our focus is determining the appropriate size of the time window. We use a Kalman filter [14, 18] that smooths regression model residuals associated with a change detection CUSUM method [2, 4, 10]. The Kalman filter is widely used in aeronautics and engineering for two main purposes: for combining measurements of the same variables but from different sensors, and for combining an inexact forecast of system's state with an inexact measurement of the state [17]. When dealing with a time series of data points $x_1, x_2, ..., x_n$ a filter computes the best guess for the point x_{n+1} taking into account all previous points and provides a correction using an inexact measurement of x_{n+1}.

The next section explains the method structure of the proposed system. The experimental evaluation is presented in section 3. In this section we apply our system to estimate the airflow of a person with Sleep Apnoea. We use the online change detection algorithm to detect changes in the airflow. Last section presents the conclusions and lessons learned.

2 Detection System in Regression Models with Kalman Filter and CUSUM

In this paper we propose a modular detection system (DSKC) for regression problems. The general framework is shown in figure 2. The system is composed by three components: a regression learning algorithm, a Kalman filter [14] and a CUSUM [2, 4]. At each iteration, the system first component, the learning algorithm, receives one unlabeled example, x_i, and then the actual model predicts, $\hat{y}_i$. After the model forecast, it receives an input from the environment, y_i and calculates the residual $r_i = |y_i - \hat{y}_i|$. The system uses r_i and the Kalman filter error estimate of the actual model, $\hat{r}_{i-1}$, to compute a residual for the dispersion, $rd_i = |r_i - \hat{r}_{i-1}|$. The Kalman filter, the system second component, receives both