Dataset: Rare Event Classification in Multivariate Time Series

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\textbf{Abstract.} A real world dataset is provided from a pulp-and-paper manufacturing industry. The dataset comes from a multivariate time series process. The data contains a rare event of paper break that commonly occurs in the industry. The data contains sensor readings at regular time-intervals (x's) and the event label (y). The primary purpose of the data is thought to be building a classification model for early prediction of rare event. However, it can also be used for multivariate time series data exploration and building other supervised and unsupervised models.

\textbf{Keywords:} multivariate time series · real world data · rare event · classification

1 Problem

A multivariate time series (MTS) is produced when multiple interconnected streams of data are recorded over time. They are commonly found in manufacturing processes that have several interconnected sensors collecting the data over time. In this problem, we have a similar multivariate time series data from a pulp-and-paper industry with a rare event associated with them. It is an unwanted event in the process a paper break, in our case that should be prevented. The objective of the problem is to

1. predict the event before it occurs, and
2. identify the variables that are expected to cause the event (in order to be able to prevent it).

2 Data

We provide a data from a pulp-and-paper mill. An example of a paper manufacturing machine is shown in Figure 1. These machines are typically several meters long that ingests raw materials at one end and produces reels of paper as shown in the picture.

Several sensors are placed in different parts of the machine along its length and breadth. These sensors measure both raw materials (e.g. amount of pulp
fiber, chemicals, etc.) and process variables (e.g. blade type, couch vacuum, rotor speed, etc.). Paper manufacturing can be viewed as a continuous rolling process. During this process, sometimes the paper breaks. If a break happens, the entire process is stopped, the reel is taken out, any found problem is fixed, and the production is resumed. The resumption can take more than an hour. The cost of this lost production time is significant for a mill. Even a 5% reduction in the break events will give a significant cost saving for a mill. The objective of the given problem is to predict such breaks in advance (early prediction) and identify the potential cause(s) to prevent the break. To build such a prediction model, we will use the data collected from the network of sensors in a mill. This is a multivariate time series data with break as the response (a binary variable).

The provided data has,

- 18,398 records.
- Columns:
  - time: the timestamp of the row
  - y: the binary response variable. There are only 124 rows with $y = 1$, rest are $y = 0$.
  - x1-x61: predictor variables. All the predictors are continuous variables, except x28 and x61. x61 is a binary variable, and x28 is a categorical variable. All the predictors are centered. Besides, the predictors are a mixture of raw materials and process variables. Their descriptions are omitted for data anonymity.

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## 3 Challenges

### Early classification
The cause of rare event in the problem is usually instant. For example, a machine failure happens almost instantly after a bolt breaks. Predicting such events before it occurs is thus extremely challenging. However, early detection of a failure is critical to prevent it. Similar problem is also found EEG/ECG patient data in hospitals where identifying its abnormalities as soon as possible could offer doctors an emergency alarm and time to save the patient. He et. al. (2015) [1] is a good reference to further understand the challenges of an early MTS classification problem.

One straightforward approach you may consider for formulating an early classification problem is: move the class column up by \( k \) rows. That is, make \( y_{t-k} \leftarrow y_t \), where \( k = 1, 2, \ldots \). In this problem, it is recommended to keep \( k \) no more than 2. If \( k = 1 \), we are predicting the event one time unit (equal to 2 mins in the given data) ahead.

**Feature engineering**

A deep learning approach is usually able to automatically identify important features. However, it requires large amount of data which is a limitation in our problem. Therefore, an appropriate feature engineering becomes critical in developing an effective approach for this problem. Schfer and Leser (2017) [2] have elucidated and addressed some major challenges in this regard with a new approach. For example, multivariate time series adds large amounts of irrelevant data and noise, and a high dimensional problem due to several derived features for each time series in the data.

Schfer and Leser (2017) have proposed several features. In addition to them, a second derivative of the predictors can also be tried. This is because the first derivative, proposed in Schfer and Leser (2017), represents gradual change in a variable. A gradual change may not necessarily trigger the event. Sometimes, a sudden change, represented by a second derivative, may cause the event. E.g. in a paper machine there several rollers rotating in sync. A gradual change in the rotational frequency is less likely to cause a break than a sudden out-of-sync change.

Besides, the change in the level of the categorical variable, \( x_{28} \), may be more important than its actual value. This variable is related to the type of paper produced at that time. For this prediction model, it might be more important to capture any change in the paper type instead of the actual type of the paper. May consider adding a feature capturing the change in \( x_{28} \), e.g. \( x_{28_t} - x_{28_{t-1}} \).

**Rare event prediction**

Events, such as failures, are not frequent. Due to this the observed data is usually severely unbalanced. This severely affects the precision and recall of a classification model.

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5 Download link

The data can be downloaded from [here](#). Follow the access instructions on the link.

References

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