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Curve Forecast with the SOM Algorithm : Using a Tool to Follow the Time on a Kohonen Map

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Abstract. To forecast a complete curve, we propose a method that consists to predict from a rule based on a classification, which takes the present time class into account. This technique is simpler than a vectorial prediction and solves some problems of long term forecasting. A type of error, which belongs to this method, imposes to take care of it. The SOM and a tool of visualization that permits to follow the time on that kind of classification give us a way to control it. The application to the polish electrical consumption is presented.

1 Introduction

A first paper [5,3] explained that the prediction of a curve with the same quality for all values is a problem for recursive and vectorial methods. As each predicted value is presented to compute its future, the estimation becomes worth and worth as the future is far. The behavior of series created with a multilayer perceptron recurrence equation is chaotic and strongly dependant on the initial values. So a multilayer perceptron cannot be used in long term forecasting ([10,12,13,4]). The vectorial methods forecast all the curve values at the same time and with the same quality but would have to take into account the dependence of values, and lead to very costly algorithms.

A method that uses a classification was firstly proposed in [6]. The one that we propose in [5,14,15] gives the same importance to the complete information to forecast the future. We propose here the same type of approach but considering the present information. We use the example of Polish Electrical Consumption as a support to present the method. We thank Professor Osowski from Warsaw Technical University for giving us at disposal this data.

2 The Method:

Let us consider a time series $X(t, i)$, with a double indexation. The time is denoted by (t, i), where t is the slow scale (the day for example), and i is the rapid one (the hour for example). For each $t \in \{1,\dots,T\}$ the second index takes its values between 1 and I, where I does not depend on t. The successive values are grouped according to the t index, and we set $X(t) = (X(t, i), i = 1, \dots, I)$

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We first make a classification of all the curves X (t) into U classes C_u, each one being represented by its centroid G_u. For each class C_u, we can define the empirical probability $P_u(u')$ for the future curve ($X(t+1)$ is the future of $X(t)$) of an individual of C_u to be classified in the class $C_{u'}$.

$$P_u(u') = \frac{\sum_{t=1}^{T} 1_{\{X_t \in C_u, \quad X_{t+1} \in C_{u'}\}}}{\sum_{t=1}^{T} 1_{\{X_t \in C_u\}}}$$

, where $1_{\{proposition\}}$ is 1 or 0 when the *proposition* is true or false.

Then the estimation of the complete curve $X(t+1)$ when $X(t)$ is classified in the class u is given by:

$$\hat{X}(t+1) = \sum_{u'=1}^{U} P_u(u')\, G_{u'} \qquad (1)$$

$\hat{X}(t+1)$ can be seen as a barycenter of some convenient G_u.

3 A Problem of this Technique:

This approach suffers a typical problem illustrated by the following example. Suppose that we have 3 classes C_1, C_2, C_3 represented by the vectors G_1=(1, 0), G_2=(1/2, 1/2) G_3=(0, 1). The following table shows the repartition of the 3 class futures. C_1 future is C_1 or C_3, but never C_2.

$X(t)\backslash X(t+1)$	C_1	C_2	C_3
C_1	50%	0%	50%
C_2	0%	100%	0%
C_3	50%	0%	50%

The rule (1) predicts the future of the element in C_1 by

$$\hat{X}(t+1) = \frac{1}{2}G_1 + \frac{1}{2}G_3 = \left(\frac{1}{2}, \frac{1}{2}\right) = G_2$$

and $\hat{X}(t+1)$ is classified in C_2, which is contradictory with the previous table.

4 Solution of the Problem: The Neighborhood Notion in the SOM.

If vectors G_u in expression (1) are neighbor, the barycenter $\hat{X}(t+1)$ is closed to each of them. At the contrary, if they are far from each other, $\hat{X}(t+1)$ is far from them. The Kohonen algorithm [7,8,9,1,2] defines a neighborhood structure between the classes that we can use to solve the previous problem.

A tool to follow the time on the SOM map: presentation of the polish electrical consumption

We present the application of the forecasting rule (1) and the tool to follow the future on a Kohonen map in a real example: The hourly Polish Power (expressed in 20 000 Mwh) from 01/01/1986 to 31/12/1994. This data set was kindly lent by Pr. Osowski from Warsaw Technical University.

In a precedent study [14,15], we justified to separate the daily information $Y(t)$ into three parts, the mean $m(t)$, the standard deviation $s(t)$ and the profile $X(t)$. So we had the relation: $Y(t)= m(t) + s(t)\ X(t)$ The profile was predicted with a rule issued from a classification and the two other parameters were forecasted with classical methods such as ARMA models or Multilayer Perceptron. Here we are going to use the rule (1) to predict the future of the profiles.

We consider a cylindrical Kohonen 10 x 10 network, where left and right borders are neighbor. We train it with all the profiles.

The first map shows the class centroids, the second all the curves of a class in its corresponding unit. So we can control if the vectors used in expression (1) are neighbor. Now we need a tool to visualize where the (t+1) day is classified when the (t) one belongs to class u.

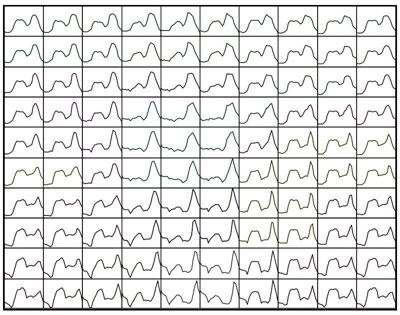

Figure 1:

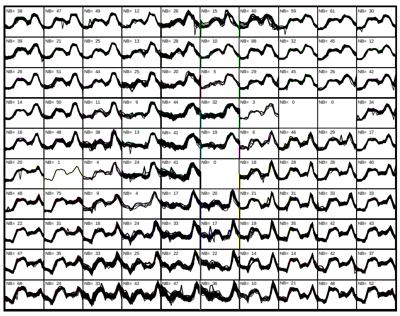

Figure 2

The tool:

Let us extract the individuals of the class u and build the set E^u of their following days (let us take for example the unit 32).

$$E^u = \{X(t+1) / X(t) \in C_u\}$$

The map in figure 3, called *future of the class* u=32, represents the repartition of E^u into the U Kohonen classes. The unit u' is white, gray light, gray or black when *an individual of* E^u *is classified in u' with the frequency* respectively 0%, between 0% and 20%, between 20% and 40%, more than 40%. We can see that most of the units are empty and the others are closed on the map. We can represent such a figure for all the units and we chose to arrange them on the Kohonen map, as in figure 4, in order to visualize all the class futures and to be able to compare ones to others.

5. The Prediction of Polish Power.

To explain the future, the *future map* is not sufficient (some areas are not connected). The figure 5 presented in [14,15,16], which projects the *kind of day* on the map, shows that Thursday and Friday have the same classification, but not the same future. So, we have to introduce in the rule (1) the variable *kind of day* with 3 modalities k: Friday, Saturday and other days, as follow:

$$P_{u,k}(u') = \frac{\sum_{t=1}^{T} 1_{\{X_t \in C_u,\ t \text{ has the kind of day } k,\ X_{t+1} \in C_{u'}\}}}{\sum_{t=1}^{T} 1_{\{X_t \in C_u,\ t \text{ has the kind of day } k\}}} \qquad (1')$$

Let us compare this approach (class of time t, *kind of day*) with the one presented in [14,15] (*kind of month*, *kind of day*) which rule does not give importance to what happens today to forecast tomorrow:

$$P_{m,k}(u') = \frac{\sum_{t=1}^{T} 1_{\{\text{month of } t \text{ is } m,\ t \text{ has the kind of day } k,\ X_{t+1} \in C_{u'}\}}}{\sum_{t=1}^{T} 1_{\{\text{month of } t \text{ is } m,\ t \text{ has the kind of day } k\}}}$$

By computing the error E, $E = \frac{1}{N} \times \frac{1}{24} \times \sum_{t=1}^{T} \sum_{i=1}^{I} \left(X_t^i - \hat{X}_t^i\right)^2$

we obtain 0.0038 for the present method, when we got 0.0040 with the previous one:

6. Conclusion:

The error is about the same but we have to consider that the approaches are different. More than that, they can be mixed to have a prediction more precise or more robust. The visualization of future solves the problem explained in section 3. As an evolution, we can also introduce the information of the previous week as the (t-7) class.

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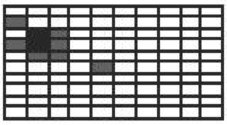

Figure 3

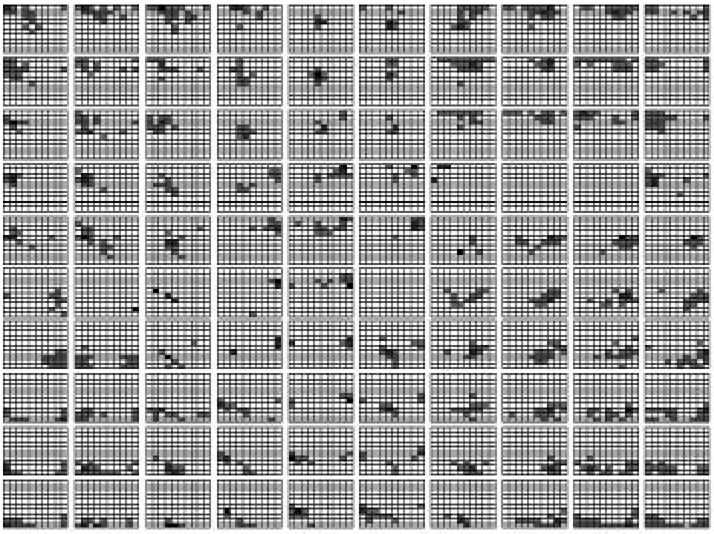

Figure 4

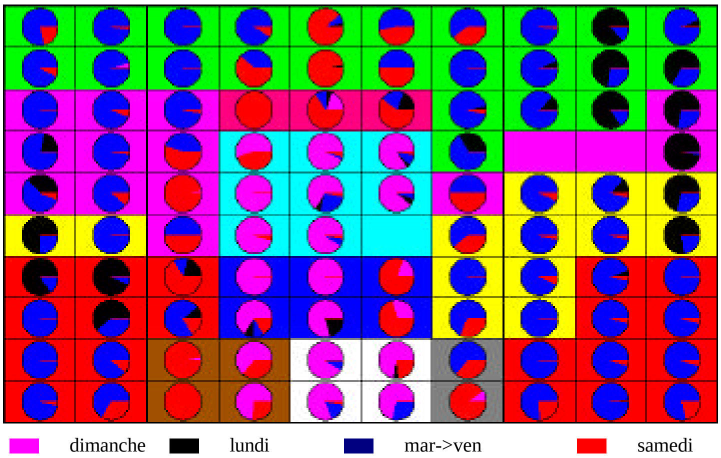

Figure 5

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