CO^2RBFN for Short and Medium Term Forecasting of the Extra-Virgin Olive Oil Price

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Abstract. In this paper an adaptation of CO^2RBFN, evolutionary COoperative-COmpetitive algorithm for Radial Basis Function Networks design, applied to the prediction of the extra-virgin olive oil price is presented. In this algorithm each individual represents a neuron or Radial Basis Function and the population, the whole network. Individuals compite for survival but must cooperate to built the definite solution. The forecasting of the extra-virgin olive oil price is addressed as a time series forecasting problem. In the experimentation medium-term predictions are obtained for first time with these data. Also short-term predictions with new data are calculated. The results of CO^2RBFN have been compared with the traditional statistic forecasting Auto-Regressive Integrated Moving Average method and other data mining methods such as other neural networks models, a support vector machine method or a fuzzy system.

1 Introduction

Radial Basis Function Networks (RBFNs) are an important artificial neural network paradigm [5] with interesting characteristics such as a simple topological structure or universal approximation ability [23]. The overall efficiency of RBFNs has been proved in many areas such as pattern classification [6], function approximation [23] or time series prediction [31].

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An important paradigm for RBFN design is the Evolutionary Computation [3], a general stochastic optimization framework inspired by natural evolution. Typically, in this paradigm each individual represents a whole network (Pittsburgh scheme) that is evolved in order to increase its accuracy.

CO^2RBFN [25] is a evolutionary cooperative-competitive method for the design of RBFNs. In this algorithm each individual of the population represents an RBF and the entire population is responsible for the final solution. The individuals cooperate towards a definitive solution, but they must also compete for survival.

In this paper CO^2RBFN is adapted to solving time series forecasting problems. Concretely a short and medium term forecasting of the extra virgin olive oil price is addressed.

The results obtained using CO^2RBFN are also compared with ARIMA methodology and other hybrid intelligent systems methods such as a Fuzzy System developed with a GA-P algorithm (FuzzyGAP)[28], a MultiLayer Perceptron Network trained using a Conjugate Gradient learning algorithm (MLPConjGrad)[22], a support vector machine (NU-SVR)[9], and a classical design method for Radial Basis Function Network learning (RBFNLMS)[32].

This paper is organized as follows: section 2 discusses generalities about the extra-virgin olive oil price and its prediction, describes the classical ARIMA method and reviews the RBFN design for forecasting problems. In section 3 the extension of CO^2RBFN to time series forecasting is presented. The study and results obtained for the forecast methods are detailed in Section 4. In Section 5, conclusions and future works are outlined.

2 Background

Olive oil has become an important business sector in a continuously expanding market. In 2009, World produced 2,888,000 of tons of olive oil[1], Spain is the first olive oil producing and exporting country and Jaén is the most productive province of Spain, it made 430,000 of tons, the 15% of the total production in the planet.

Agents involved in this sector are interested in the use of forecasting methods for the olive price. This is especially important in the official Market for the negotiation of futures contracts for olive oil (MFAO): a society whose objective is to negotiate an appropriate price for the olive oil at the moment it is to be sold at a fixed time in the future. An accurate prediction of this price in the future could increase the global benefits. In this context, the data provided for the design of the prediction system are the weekly extra-virgin olive oil prices obtained from *Poolred*[2], an initiative of the Foundation for the Promotion and Development of the Olive and Olive Oil located in Jaén, Spain.

The data are a set of regular time-ordered observations of a quantitative characteristic of an individual phenomenon taken at successive periods or points of time, called time series. The problems in which the data are not independent but also have

[1] http://www.mfao.es
[2] http://www.oliva.net/poolred/

a temporal relationship are called time series forecasting problems. Time series forecasting is an active research area and typical paradigm for evaluating it are statistic models [13], such as ARIMA, and data mining methods.

ARIMA [4] stand for Auto-Regressive Integrated Moving Average, a group of techniques for the analysis of time series which generate statistical forecasting models under the assumption of linearity among variables. Data mining is a research area concerned with extracting non-trivial information contained in a database, and has also been applied to time series forecasting. Among data mining techniques, mainly neural networks [8][15][26][30] and fuzzy rule based systems [2][17][18][19][33] have been applied to this kind of problem. In these papers, the presented forecasting problems are mainly addressed as regression problems (see section 4).

Examples of evolutive RBFN design algorithms applied to time series forecasting can be found in [7][12][21][27][29]. However, there are very few algorithms based on cooperative competitive strategies.

The authors have developed a hybrid cooperative-competitive evolutionary proposal for RBFN design, CO^{2}RBFN, applied to the classification problem [25] and have addressed the short-term forecasting of the extra virgin olive oil price [24]. This paper analyzes new data (until December 2008) of this oil price and deals with not only a short-term but also with a new medium-term forecasting of the extra virgin olive oil price, of these new data.

3 CO^{2}RBFN for Time Series Forecasting

CO^{2}RBFN [25], is an hybrid evolutionary cooperative-competitive algorithm for the design of RBFNs. As mentioned, in this algorithm each individual of the population represents, with a real representation, an RBF and the entire population is responsible for the final solution. The individuals cooperate towards a definitive solution, but they must also compete for survival. In this environment, in which the solution depends on the behavior of many components, the fitness of each individual is known as credit assignment. In order to measure the credit assignment of an individual, three factors have been proposed: the RBF contribution to the network output, the error in the basis function radius, and the degree of overlapping among RBFs.

The application of the operators is determined by a Fuzzy Rule-Based System. The inputs of this system are the three parameters used for credit assignment and the outputs are the operators' application probability.

The main steps of CO^{2}RBFN, explained in the following subsections, are shown in the pseudocode in Figure 1.

RBFN initialization. To define the initial network a specified number m of neurons (i.e. the size of population) is randomly allocated among the different patterns of the training set. To do so, each RBF centre, $\mathbf{c}_i$, is randomly established to a pattern of the training set. The RBF widths, d_i, will be set to half the average distance between the centres. Finally, the RBF weights, w_{ij}, are set to zero.

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1. Initialize RBFN
2. Train RBFN
3. Evaluate RBFs
4. Apply operators to RBFs
5. Substitute the eliminated RBFs
6. Select the best RBFs
7. If the stop condition is not
     verified go to step 2
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Fig. 1 Main steps of CO^{2}RBFN

RBFN training. The Least Mean Square algorithm [32] has been used to calculate the RBF weights. This technique exploits the local information that can be obtained from the behaviour of the RBFs.

RBF evaluation.A credit assignment mechanism is required in order to evaluate the role of each RBF ϕ_i in the cooperative-competitive environment. For an RBF, three parameters, a_i ,e_i ,o_i are defined:

- The contribution, a_i, of the RBF ϕ_i, $i = 1 \ldots m$, is determined by considering the weight, w_i, and the number of patterns of the training set inside its width, pi_i. An RBF with a low weight and few patterns inside its width will have a low contribution:
$$a_i = \begin{cases} |w_i| & if \quad pi_i > q \\ |w_i| * (pi_i/q) & otherwise \end{cases} \tag{1}$$
where q is the average of the pi_i values minus the standard deviation of the pi_i values.
- The error measure, e_i, for each RBF ϕ_i, is obtained by calculating the Mean Absolute Percentage Error (MAPE) inside its width:
$$e_i = \frac{\sum_{\forall p_i} \left| \frac{f(p_i) - y(p_i)}{f(p_i)} \right|}{npi_i} \tag{2}$$
where $f(p_i)$ is the output of the model for the point p_i, inside the width of RBF ϕ_i, $y(p_i)$ is the real output at the same point, and npi_i is the number of points inside the width of RBF ϕ_i.
- The overlapping of the RBF ϕ_i and the other RBFs is quantified by using the parameter o_i. This parameter is computed by taking into account the fitness sharing methodology [11], whose aim is to maintain the diversity in the population. This factor is expressed as:
$$o_i = \sum_{j=1}^{m} o_{ij} \tag{3}$$
where o_{ij} measures the overlapping of the RBF ϕ_i y ϕ_j $j = 1 \ldots m$.

Applying operators to RBFs. In CO^{2}RBFN four operators have been defined in order to be applied to the RBFs:

- Operator Remove: eliminates an RBF.
- Operator Random Mutation: modifies the centre and width of an RBF in a percentage below 50% of the old width.
- Operator Biased Mutation: modifies the width and all coordinates of the centre using local information of the RBF environment. The technique used follows the recommendations [10] that are similar to those used by the algorithm LMS algorithm. The error for the patterns within the radius of the RBF, ϕ_i, are calculated. For each coordinate of the center and the radius a value Δc_{ij} and Δd_i respectively are calculated. The new coordinates and the new radius are obtained by changing (increasing or decreasing) its old values to a random number (between 5% and 50% of its old width), depending on the sign of the value calculated.

$$\Delta d_i = \sum_k e(\overrightarrow{p_k}) \cdot w_i \tag{4}$$

where $e(\overrightarrow{p_k})$ is the error for the pattern $\overrightarrow{p_k}$.

$$\Delta c_{ij} = sign(c_{ij} - p_{kj}) \cdot e(\overrightarrow{p_k}) \cdot w_i \tag{5}$$

- Operator Null: in this case all the parameters of the RBF are maintained.

The operators are applied to the whole population of RBFs. The probability for choosing an operator is determined by means of a Mandani-type fuzzy rule based system [20] which represents expert knowledge about the operator application in order to obtain a simple and accurate RBFN. The inputs of this system are parameters a_i, e_i and o_i used for defining the credit assignment of the RBF ϕ_i. These inputs are considered as linguistic variables va_i, ve_i and vo_i. The outputs, p_{remove}, p_{rm}, p_{bm} and p_{null}, represent the probability of applying Remove, Random Mutation, Biased Mutation and Null operators, respectively.

Table 1 shows the rule base used to relate the described antecedents and consequents. In the table each row represents one rule. For example, the interpretation of the first rule is: If the contribution of an RBF is Low Then the probability of applying the operator Remove is Medium-High, the probability of applying the operator

Table 1 Fuzzy rule base representing expert knowledge in the design of RBFNs

Antecedents				Consequents				Antecedents				Consequents			
	v_a	v_e	v_o	p_{remove}	p_{rm}	p_{bm}	p_{null}		v_a	v_e	v_o	p_{remove}	p_{rm}	p_{bm}	p_{null}
R1	L			M-H	M-H	L	L	R6		H		M-H	M-H	L	L
R2	M			M-L	M-H	M-L	M-L	R7			L	L	M-H	M-H	M-H
R3	H			L	M-H	M-H	M-H	R8			M	M-L	M-H	M-L	M-L
R4		L		L	M-H	M-H	M-H	R9			H	M-H	M-H	L	L
R5		M		M-L	M-H	M-L	M-L								

Random Mutation is Medium-High, the probability of applying the operator Biased Mutation is Low and the probability of applying the operator null is Low.

Introduction of new RBFs. In this step, the eliminated RBFs are substituted by new RBFs. The new RBF is located in the centre of the area with maximum error or in a randomly chosen pattern with a probability of 0.5 respectively.

The width of the new RBF will be set to the average of the RBFs in the population plus half of the minimum distance to the nearest RBF. Its weights are set to zero.

Replacement strategy. The replacement scheme determines which new RBFs (obtained before the mutation) will be included in the new population. To do so, the role of the mutated RBF in the net is compared with the original one to determine the RBF with the best behaviour in order to include it in the population.

4 Experimentation and Results

The dataset used in this work have been obtained from *Poolred*[3], an initiative of the Foundation for the Promotion and Development of the Olive and Olive Oil located in Jaén, Spain. The time series dataset contains the weekly extra-virgin olive oil price per kilogram.

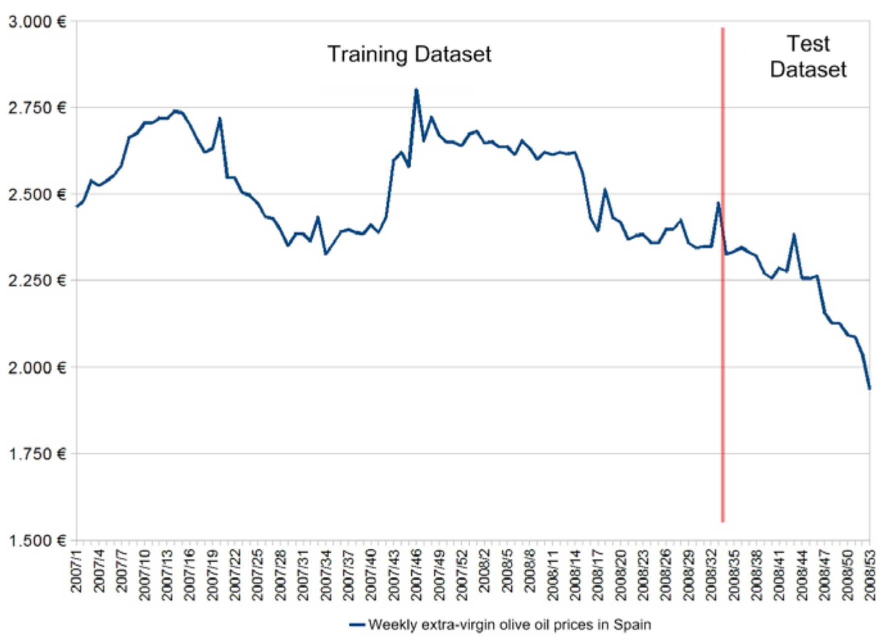

Fig. 2 Weekly extra-virgin olive oil prices in Tons / Euro

[3] http://www.oliva.net/poolred/

The task addressed in this work is that of performing two forecast next week and four weeks later of the extra-virgin olive oil price. In this study, the data used are from the 1^{st} week of the year 2007 to the 53^{nd} week of the year 2008 in Spain. The cases in the data set were divided into two subsets: one for training and the other for testing. The data from the 1^{st} week of 2007 to the 33^{th} week of 2008 were used for training. The performance of the different forecastings and methods were tested by estimating the data from the 34^{nd} week to the 53^{nd} week of 2008. Figure 2 shows the time series data and training and test datasets.

As mentioned, experiments carry out predictions with horizons of one week and four weeks. In this way the patterns are heuristically composed of: $(n-3, n-2, n-1, n, n+1)$, when the price to forecast is $n+1$ and must be determined from the past prices $n-3$ to n; $(n-3, n-2, n-1, n, n+4)$, when the price to forecast is $n+4$ and must be determined from the past prices $n-3$ to n.

To estimate prediction capacity, the error considered is the Mean Absolute Percentage Error (MAPE):

$$MAPE = \sum_{i}^{n}(\mid (f_i - y_i)/f_i \mid) \tag{6}$$

where f_i is the predicted output of the model and y_i is the desired output.

Other methods used in the experimentation are:

- ARIMA models, also called Box-Jenkins models [4], predict variable's present values from its past values. The development of an ARIMA methodology consists of the search for an ARIMA(p,d,q) model, which is able to generate the time series object of the study. Here p is the value for the auto-regressive parameter, d is the order of differentiation and q is the moving average parameter. ARIMA modeling involves the follow stages: (1) Identification of the model or the initial p, d, and q parameters; (2) Estimation of the p and q parameters; (3) Diagnosis of the residuals in order to investigate model adequacy.
- FuzzyGAP method [28]. A GA-P method [16] uses an evolutionary computation method, a hybrid between genetic algorithms and genetic programming, and optimized to perform symbolic regressions. Each element comprises a chain of parameters and a tree which describes a function, depending on these parameters. The two operators by means of which new members of the population are generated are crossover and mutation. In the GA-P algorithm both operations are performed independently over the tree and the parameter chain.
- MLPConjGrad [22]. MLPConjGrad uses the conjugate-gradient algorithm to adjust weight values of a multilayer perceptron [14]. Compared to gradient descent, the conjugate gradient algorithm takes a more direct path to the optimal set of weight values. Usually, the conjugate gradient is significantly faster and more robust than the gradient descent. The Conjugate gradient also does not require the user to specify learning rate and momentum parameters.
- RBFN-LMS. Builds an RBFN with a pre-specified number of RBFs. By means of the K-Means clustering algorithm it chooses an equal number of points from the training set to be the centres of the neurons. Finally, it establishes a single

radius for all the neurons as half the average distance between the set of centres. Once the centres and radio of the network have been fixed, the set of weights is analytically computed using the LMS algorithm [32].

- NU-SVR, the SVM (Support Vector Machine) model uses the sequential minimal optimization training algorithm and treats a given problem in terms of solving a quadratic optimization problem. The NU-SVR, called also v-SVM, for regression problems is an extension of the traditional SVM and it aims to build a loss function [9].

Table 2 ARIMA Model Summary

Parameter	Estimate	Stnd.Error	P-Value
AR(1)	0,906789	0,0461258	0,000000
Mean	2,52871	0,0612143	0,000000

For the ARIMA model has been estimated an ARIMA (1,0,0). In table 1, the Maximum Likelihood Estimation, Standard Errors and P-Values are shown for the parameters of the most appropriate ARIMA model which is fitted to the price time series. When considering the 85 observations the difference equation for the AR(1) model is written as

$$(1-0.906789B)(X_t-2.52871)=\varepsilon_t, \tag{7}$$

with ε_t, $t=1,\ldots,n$ the white noise term. The third column in table 1 summarizes the statistical significance of the terms in the forecasting model. Terms with P-Value less than 0.05 are statistically significantly different from zero at 95% confidence level. The P-Value for AR(1) term is less than 0.05, so it is significantly different from 0. In the case of the constant term the P-Value has a similar behavior.

The implementations of the rest data mining methods have been obtained from KEEL [1]. The parameters used in these data mining methods are the values recommended in the literature. For CO^2RBFN the number of executions is 200 and the number of RBFs or individuals in the population is set to 10.

The series have been differentiated to avoid problems related with the stationarity. The predictions have been performed using the differenced data, but errors have been calculated after reconstruct the original series.

The traditional work mode of ARIMA (without updating) is predicting the first value, and then calculate the following values using their own predictions. So it can accumulate a error if the number of test dataset is greater than six or eight samples. That's why for ARIMA work in circumstances similar to the methods of data mining, we will "update" data from test simulating the data mining models. For four weeks forecasting, ARIMA only can use its own predictions with updating.

To obtain the results, algorithms have been executed 10 times and in Table 3 shows the average error MAPE mission and its standard deviation. The figures 3 and 4 show the best prediction achieved by the methods for the test set.

Table 3 Results obtained by different methods forecasting the price of olive oil

Method	MAPE for 1 week forecasting	MAPE for 4 weeks forecasting
Fuzzy-GAP	0,02170 ± 0,00226	0,03536 ± 0,00461
MLP ConjGrad	0,02052 ± 0,00041	0,02970 ± 0,00196
NU-SVR	0,01936 ± 0	0,03003 ± 0
RBFN-LMS	0,02111 ± 0,00234	0,04706 ± 0,00901
ARIMA (without updating)	0,13036 ± 0	-
ARIMA updating	0,02823 ± 0	0,06827 ± 0
CO^{2}RBFN	0,01914 ± 0,00057	0,03230 ± 0,00160

If we analyze the results we can draw the following conclusions:

- The data mining methods have better performance that ARIMA models, which were traditionally used in econometrics to predicting this kind of problem.
- This superiority of data mining methods over ARIMA is even clearer when using ARIMA with traditional methodology (without updating).
- The method proposed by the authors, CO^{2}RBFN, is the best method when the horizon of prediction is one week and is close to the top spot in the forecasting to four weeks.
- CO^{2}RBFN has practically the lowest standard deviation of all non-deterministic methods, which demonstrates the robustness of the method.

Finally, it must be highlighted that the accuracy of the results obtained has been of interest to olive-oil sector experts.

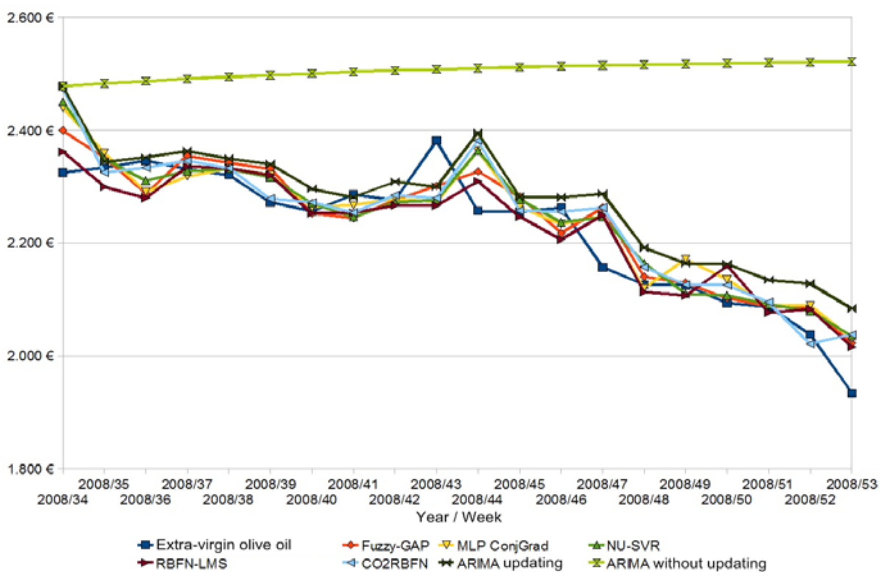

Fig. 3 Forecasting of the best repetition reached by different methods for one week

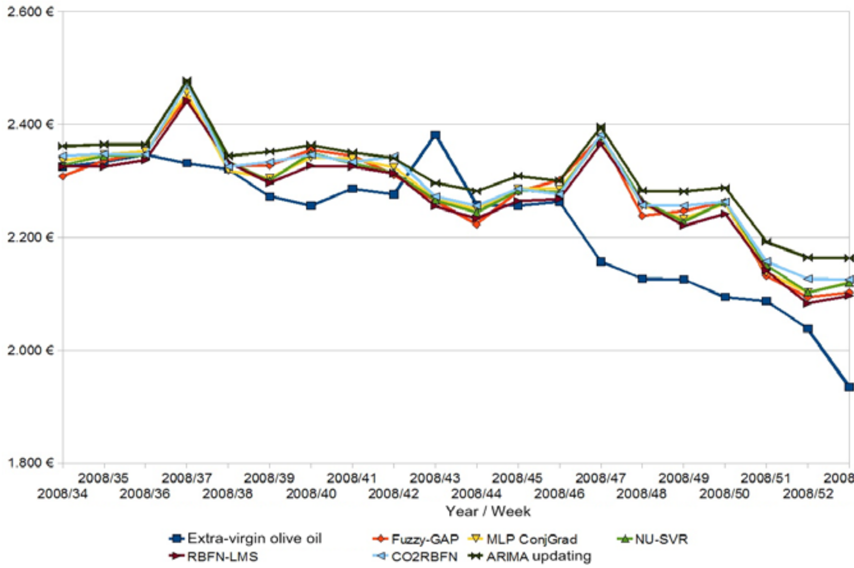

Fig. 4 Forecasting of the best repetition reached by different methods for four weeks

5 Concluding Remarks

This paper presents an application of an evolutionary cooperative-competitive algorithm (CO^2RBFN) to the forecasting of the extra-virgin olive oil price. As important key point of our proposal it is must be highlighted the identification of the role (credit assignment) of each basis function in the whole network. It is defined by three factors are defined and used: the RBF contribution to the network's output, a_i; the error in the basis function radius, e_i; and the degree of overlapping among RBFs, o_i. Another important key is that the application of the evolutive operators is determined by a fuzzy rule-based system which represents expert knowledge of the RBFN design. The inputs of this system are the three parameters used for credit assignment.

A new medium horizon, four weeks, along with a short horizon, one week, have been defined for the forecasting of the extra-virgin olive oil weekly price. The results of CO^2RBFN have been compared with the ones obtained by the well-known classical statistical ARIMA method and a set of reliable data mining methods. The data mining methods applied for the comparison are: MLPConjGrad, a multilayer perceptron network which trains which a conjugate gradient algorithm; FuzzyGAP, a fuzzy system developed with a GA-P algorithm; NU-SVR, a support vector machine method, and RBFNLMS, a radial basis function network trained with the LMS algorithm.

From the results it can be concluded that datamining methods outperforms ARIMA methodology and that CO^2RBFN is the best method in the prediction to one week and is close to the top spot in the forecasting to four weeks. Also lowest standard deviation of CO^2RBFN demonstrates the robustness of the method.

As future lines, pre-processing for feature selection and exogenous features like meteorology or econometric data can be taken into account in order to increase the performance of the forecast.

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