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Interval type-3 fuzzy aggregators for ensembles of neural networks in COVID-19 time series prediction

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A B S T R A C T

In this work we are presenting an approach for fuzzy aggregation in ensembles of neural networks for forecasting. The aggregator is used in an ensemble to combine the outputs of the networks forming the ensemble. This is done in such a way that the total output of the ensemble is better than the outputs of the individual modules. In our approach a fuzzy system is used to estimate the weights that will be assigned to the outputs in the process of combining them in a weighted average calculation. The uncertainty in the process of aggregation is modeled with interval type-3 fuzzy, which in theory can outperform type-2 and type-1. Publicly available data sets of COVID-19 cases for several countries in the world were utilized to test the proposed approach. Simulation results of the COVID-19 data show the potential of the approach to outperform other aggregators in the literature.

1. Introduction

Fuzzy logic has become very important in different disciplines of study, one of the areas in which we focus for this work is the time series prediction area, as it has been shown in the literature that the use of fuzzy logic helps to improve results in many problems (Zadeh, 1989, 1998). Type-1 evolved to type-2 fuzzy systems mainly with the works by Mendel in 2001 (Mendel, 2001). Initially, interval type-2 fuzzy systems were studied and applied to several problems (Mendel, 2001). Later, these systems were applied to many problems in areas such as: robotics, control, diagnosis and others (Mendel, 2017; Karnik and Mendel, 2001). Simulation and experimental results show that interval type-2 outperforms type-1 fuzzy systems in situations with higher levels of noise, dynamic environments or highly nonlinear problems (Moreno et al., 2020; Mendel et al., 2014; Olivas et al., 2016). Later, general type-2 fuzzy systems were considered to manage higher levels of uncertainty, and good results have been achieved in several areas of application (Sakalli et al., 2021; Ontiveros et al., 2018; Castillo and Amador-Angulo, 2018). More recently, it is becoming apparent that type-3 fuzzy systems could help solve even more complex problems. For this reason, in this paper we are putting forward the basic constructs of type-3 fuzzy systems by extending the ideas of type-2 (Cao et al., 2021; Mohammadhodaei et al., 2021; Qasem et al., 2021), and also applying them for time series prediction.

Recently, the very rapid propagation of COVID-19 has been noticed, including its several waves, that has spread to all continents in the world. In particular, in the case of Europe several countries, like Italy, Spain, and France have been hit hard with the spread of the COVID-19 virus, having a significant number of confirmed cases and deaths (The Humanitarian Data Exchange (HDX), 2022; Shereen et al., 2020; Sohrabi et al., 2020; Apostolopoulos and Bessiana, 2020; Sarkodie and Owusu, 2020; Beck et al., 2020). In the case of the American continent, United States, Canada and Brazil have also suffer a significant number of cases due to the rapid spread of COVID-19 (Zhong et al., 2020; Kamel Boulou and Geraghty, 2020; Gao et al., 2020). There are also several recent works on predicting and modeling COVID-19 behavior in space and time (Rao and Vazquez, 2020; Melin et al., 2020a). However, still the prediction problem remains a challenging task, as can be seen in recent papers on this topic (Melin et al., 2020b; Jin et al., 2020; Khalilpourazari et al., 2021; Kuvvetli et al., 2021; Liu et al., 2022), where different methods have been utilized, such as neural networks and fuzzy logic for achieving this task. In this sense, we can say that this was the main motivation for undertaking this research work.

As a difference to previous prediction approaches, one of the key contributions of this work is the proposal of mathematical definitions of interval type-3 fuzzy theory, which were obtained by using the extension principle on the type-2 fuzzy theory definitions. In addition, the utilization of interval type-3 fuzzy, in the aggregation of ensemble outputs for prediction, has not been previously presented in the literature, and it is now shown that interval type-3 has the potential to be better than type-2 and type-1 in prediction problems. Also,
the hybrid of type-3 with ensemble of neural networks has not been previously considered in prediction problems. We consider that these are important contributions to the frontier knowledge in soft computing and its applications.

The structure of this article is defined as: Section 2 introduces basic terminology of interval type-3 fuzzy sets, Section 3 describes the proposed type-3 prediction method, Section 4 summarizes the results, and Section 5 outlines the conclusions and future works.

2. Interval type-3 Fuzzy logic

Interval type-3 fuzzy can be viewed as an extension of type-2 models. We offer basic terminology of type-3 fuzzy sets to give an idea of the difference with respect to their type-2 and type-1 counterparts. We start by recalling the concept of a fuzzy set (type-1) proposed by Zadeh (1965), where the membership to a set is allowed to be any number in the [0, 1] interval, in this way extending the concept of traditional sets. In this case, a type-1 fuzzy set A, is represented as:

\[ A = \{(x, \mu_A(x))\} \quad \text{for all } x \in X \]  

where \( x \) is an element of a universe \( X \), and \( \mu_A(x) \) is a membership function with numeric values in the interval [0, 1]. Later, as an extension of type-1, the concept of type-2 fuzzy sets was proposed, which allows the membership to be a type-1 fuzzy set, instead of precise number (Mendel, 2001, 2017). The goal of this extension was allowing a better representation of real-world uncertainty. A type-2 fuzzy set \( \tilde{A} \), is represented mathematically as:

\[ \tilde{A} = \{(x, \mu_{\tilde{A}}(x, u)) \mid \forall x \in X, \forall u \in J, 0 \leq \mu_{\tilde{A}}(x, u) \leq 1 \} \]

in which \( 0 \leq \mu_{\tilde{A}}(x, u) \leq 1 \). In fact, \( J \) represents the primary membership domain of \( x \), and \( \mu_{\tilde{A}}(x, u) \) is a type-1 fuzzy set known as the secondary set. Later, a type-3 fuzzy set was also proposed as an extension of a type-2 fuzzy set, by using a primary, secondary and tertiary membership functions, with the goal of having an even better representation of uncertainty. The mathematical definition of a type-3 fuzzy set can be established as follows:

**Definition 1.** A type-3 fuzzy set (T3 FS) (Rickard et al., 2009; Mohammazadeh et al., 2020; Liu et al., 2021), denoted by \( A^3 \), is represented by the plot of a trivariate function, called membership function (MF) of \( A^3 \), in the Cartesian product in \( X \), where is the universe of the primary variable of \( A^3 \), \( x \). The MF of is formulated by \( \mu_{A^3}(x, u, v) \) or for short and it is called a type-3 membership function (T3 MF) of the T3 FS,

\[ \mu_{A^3}(x, u, v) : X \times [0, 1] \times [0, 1] \rightarrow [0, 1] \]

\[ A^3 = \{(x, u(x), v(x, u), \mu_{A^3}(x, u, v)) \mid x \in X, u \in U \subseteq [0, 1], v \in V \subseteq [0, 1]\} \]

where \( x \) is the universe for the secondary variable and is the universe for tertiary variable \( v \). If the T3 MF is uniformly equal to 1 then we have an Interval type-3 fuzzy set (IT3 FS) with interval type-3 MF (IT3MF).

**Fig. 1** illustrates and IT3 FS with IT3MF \( \mu(x, u) \), where \( \mu(x, u) \) is the LMF and is the UMF. The embedded secondary T1 MFs in \( x' \) of \( A \) and \( \tilde{A} \) are \( f_1(u) \) and \( f_2(u) \).

In this case, we utilize interval type-3 MFs that are scaled Gaussians in the primary and secondary domains, respectively. This function can be represented as, \( \mu = \text{ScaleGaussScaleGaussIT3MF} \), with Gaussian footprint of uncertainty \( \text{FOU}(\lambda) \), characterized with parameters \([\sigma, m]\) (UpperParameters) for the upper membership function UMF and for the lower membership function LMF, the parameters \( \lambda \) (LowerScale), \( \ell \) (LowerLag) to form the \( \mu(x, \mu(x)) \). The vertical cuts characterize theFOU(\(\lambda\)), and are IT2 FSs with Gaussian IT2 MFs, \( \mu_{A(x)} \) with parameters for the UMF and LMF \( \lambda \) (LowerScale), \( \ell \) (LowerLag). The IT3 MF, ScaleGaussScaleGaussIT3MF(x, \([\sigma, m]\), \( \lambda \), \( \ell \)) is described with the following equations:

\[ \bar{\mu}(x) = \exp \left[ -\frac{1}{2} \left( \frac{x - m}{\sigma} \right)^2 \right] \]

\[ \underline{\mu}(x) = \lambda \cdot \exp \left[ -\frac{1}{2} \left( \frac{x - m}{\sigma} \right)^2 \right] \]

where \( \sigma^+ = \sigma \sqrt{\ln 2 / \ln e} \), \( \epsilon \), is the machine epsilon. If \( \ell = 0 \), then \( \sigma^+ = \sigma \). Then and are the upper and lower limits of the DOU. The range \( \delta(u) \), and radius, \( \sigma_\varepsilon \), of the FOU are:

\[ \delta(u) = \bar{\mu}(x) - \mu_\varepsilon(x) \]

\[ \sigma_\varepsilon = \frac{\delta(u)}{2\sqrt{3}} + \epsilon \]

The apex or core, \( m(x) \), of the IT3 MF \( \mu(x, u) \), is defined by the expression:

\[ m(x) = \exp \left[ -\frac{1}{2} \left( \frac{x - m}{\rho} \right)^2 \right] \]
where $\rho = (\rho^+ + \rho^-)/2$. Then, the vertical cuts with IT2 MF,

$$
\mu_{A(x)}^\mu (u) = \exp \left[ -\frac{1}{2} \left( \frac{u - u(x)}{\sigma_x^\mu} \right)^2 \right]
$$

(9)

and

$$
\mu_{A(x)}^\delta (u) = \lambda \cdot \exp \left[ -\frac{1}{2} \left( \frac{u - u(x)}{\sigma_x^\delta} \right)^2 \right]
$$

(10)

where $\sigma_x^\mu = \sigma_x \sqrt{\ln(\lambda/\ln(\varepsilon))}$. If $\ell = 0$, then $\sigma_x^\mu = \sigma_x$. Then, $\mu_{A(x)}^\mu (u)$ and $\mu_{A(x)}^\delta (u)$ are the UMF and LMF of the IT2 FSs of the vertical cuts of the secondary IT2MF of the IT3 FS.

3. Proposed method

The method consists of utilizing an ensemble of two neural networks and then combine their outputs with a weighted average in which the weights are computed with an interval type-3 fuzzy system. Fig. 2 illustrates the architecture of the proposed method, where we can appreciate that the time series enters the two modules of the ensemble and individual predictions $P_1$ and $P_2$ are obtained with corresponding training errors $e_1$ and $e_2$, respectively.

The fuzzy rules for aggregating the results with two modules are:

1. If ($e_1$ is small) and ($e_2$ is small), then ($w_1$ is high)($w_2$ is high).
2. If ($e_1$ is small) and ($e_2$ is medium), then ($w_1$ is high)($w_2$ is medium).
3. If ($e_1$ is small) and ($e_2$ is high), then ($w_1$ is high)($w_2$ is low).
4. If ($e_1$ is medium) and ($e_2$ is small), then ($w_1$ is medium)($w_2$ is high).
5. If ($e_1$ is medium) and ($e_2$ is medium), then ($w_1$ is medium)($w_2$ is medium).

Fig. 2. Architecture of the proposed ensemble with type-3 fuzzy response aggregation.

Fig. 3. Interval type-3 system to compute the weights.
6. If \((e_1\) is medium) and \((e_2\) is high), then \((w_1\) is medium)\((w_2\) is low).
7. If \((e_1\) is high) and \((e_2\) is small), then \((w_1\) is low)\((w_2\) is high).
8. If \((e_1\) is high) and \((e_2\) is medium), then \((w_1\) is low)\((w_2\) is medium).
9. If \((e_1\) is high) and \((e_2\) is high), then \((w_1\) is low)\((w_2\) is low).

The design of the fuzzy rules was based on general knowledge of training neural networks with time series data. It is known that a high training error means that the weight of the corresponding neural network should be low. On the other hand, if the training error is low then the weight of the network should be high. This general knowledge was used in putting forward the fuzzy rules. The interval type-3 system (seen in Fig. 3) has as inputs the error values of each neural network, \(e_1\) and \(e_2\), respectively. The fuzzy rules could be easily generalized for the case of three neural networks and correspondingly three weights. After the type-reduction and defuzzification, the Type-3 system has as outputs the corresponding weights \((w_1\) and \(w_2\)) for each neural network according to its prediction errors to obtain a final prediction.
In Table 1 we show the specific parameters of the MFs, which were found by trial and error, and could be optimized in the future with metaheuristics for achieving even better results. Basically, Table 1 shows the centers and standard deviations of the Gaussian MFs. The parameters of Table 1 are used in Eqs. (4)–(10) to generate the MFs needed for the fuzzy rules.

Regarding the lower scale ($\lambda$) and lower lag ($\lambda$) parameters, after experimentation for achieving better results, they were found to be 0.8 and 0.2 for the inputs, respectively. On the other hand, for the outputs, they were found to be 0.9 and 0.6, respectively.

In Figs. 4 and 5 we show the input MFs for both errors, respectively. In Figs. 6 and 7 we illustrate the output MFs for both weights, respectively. The actual IT3 MFs are three dimensional, but in these figures we are showing a view on the plane for simplicity. The MFs of these figures are generated by plotting Equations (4) to (10) with the parameters shown in Table 1. For example, for error $e_1$ (input 1) the parameter values of the first three rows are used in Eqs. (4) to (10) to generate...
Fig. 4. Similarly, for generating Figs. 5–7 the same process is performed. For the inputs (Figs. 4 and 5), it is assumed that the linguistic values are granulated as: small, medium or high, with Gaussian MFs.

In the outputs (Figs. 6 and 7), it is assumed that the weights are granulated into: low, medium and high. These linguistic values are modeled with Gaussian MFs.

In Fig. 8 we show one view of the nonlinear surface representing the fuzzy model, in this case, representing the relation of \( w_1 \) with respect to the errors \( e_1 \) and \( e_2 \). In Fig. 9 the view is shown for \( w_2 \) with respect to the errors.

In Fig. 10 we illustrate the inference for a particular value of one of the inputs, and then in Fig. 11 the type-reduction and defuzzification are presented.

4. Simulation results

The experiments were performed with a dataset used from the Humanitarian Data Exchange (HDX) (The Humanitarian Data Exchange (HDX), 2022), which includes COVID-19 data from countries, where cases have occurred from January 22, 2020 to January, 2022, where the last 15 days are used for the testing.

Table 2 shows the resulting errors of training the two modules of the ensemble (\( e_1 \) and \( e_2 \)) and the corresponding weights obtained by the interval type-3 system of the previous section. The results of Table 2 are for five countries: France, Germany, Japan, Poland and USA. In Table 2 we illustrate the results of combining the predicted values of modules with the weighted average equations using the weights produced by the
fuzzy system. The modules of the neural network were trained with the COVID-19 time series from January of 2020 to 2022, and the last 15 days are used for testing and comparing with the real values. Recurrent neural networks are used, with three delays, 300 training epochs, and backpropagation with momentum learning and adaptive learning rate. There are three layers in all the networks.

In Table 3 the results for the prediction of France are shown. In Table 4 we show the results for Germany and the prediction is illustrated in Fig. 12. In Table 5 we show the results for Japan and the prediction is illustrated in Fig. 13. In addition, we show in Table 6 and Fig. 14 the results for Poland. Finally, we show in Table 7 the prediction for USA.

According to Table 3 the results of the prediction for France are relatively close to the real values, validating the proposed model. The prediction results for Germany are very good according to Table 4 and can also visualized in Fig. 12, where both the forecasted and real values are plotted and can be appreciated to be very near.

The prediction results for Japan are very good according to Table 5 and can also visualized in Fig. 13, where both the forecasted and real values are plotted and can be appreciated to be very near.
According to Table 6 the predicted results for Poland for the 15 days are very close to the real values and this fact can also be appreciated in Fig. 14, where both the real and predicted values are plotted and be seen to be near.

Finally, in Table 7 we can notice once more that predicted and real values are close for the case of the United States.
In addition, we have made a comparison with the prediction of type-3 with respect to type-2 fuzzy aggregation, using the same approach of weighted averages, to show the advantage of the proposal. In Table 8 we summarize a comparison for the prediction errors for the same period of time for 12 countries in which type-3 is better with respect to type-2 fuzzy aggregation, using the same approach of weighted averages, to show the advantage of the proposal. In Table 8 we summarize a comparison for the prediction errors for the same period of time for 12 countries in which type-3 is better with respect to type-2 fuzzy aggregation, using the same approach of weighted averages, to show the advantage of the proposal.

From the previous tables we can conclude that predicting with the interval type-3 fuzzy approach for aggregation in ensemble of neural networks is a good alternative in the prediction of complex time series, like the COVID-19. Of course, the proposed approach can be extended for ensembles with more modules by using fuzzy systems with more inputs and outputs, and the design can be optimized with metaheuristics for improving results. Finally, we can also mention that the ensemble approach with fuzzy aggregation could also be used for multiple time series problems, because we can use the modules for modeling each of the time series, and then at the end use the aggregator to combine the predictions of the modules.

5. Conclusions

In this work a new approach for fuzzy aggregation in ensembles of neural networks has been utilized. The aggregator in an ensemble is utilized to combine the outputs of the networks forming the ensemble, in such a way that the total output is better than the outputs of the individual modules. In our approach a fuzzy system is used to estimate the weights that will be assigned to the outputs in the process of combining them in a weighted average calculation. The uncertainty in the process of aggregation is modeled with interval type-3. Simulation results show the potential of the approach to outperform other methods in the literature, such as type-2 and type-1 fuzzy aggregators. We have utilized COVID-19 time series of several countries to test the good performance of the proposed approach. As future work we plan to use our approach in other applications, like in Cervantes and Castillo (2015), Melin et al. (2020b), Castillo et al. (2014), Rubio et al. (2017). Also, we plan to optimize the type-3 system with metaheuristics for improving results. Finally, we can also mention that with more inputs and outputs, and the design can be optimized with metaheuristics for improving results. Finally, we can also mention that with more inputs and outputs, and the design can be optimized with metaheuristics for improving results.
other time series prediction problems. Finally, we could also consider in the future, general type-3 fuzzy models instead of interval type-3, as outlined in Castillo et al. (2022).

**CRediT authorship contribution statement**

**Oscar Castillo**: Conceptualization, Methodology, Validation, Writing – original draft. **Juan R. Castro**: Conceptualization, Validation, Formal analysis, Software. **Martha Pulido**: Conceptualization, Methodology, Validation, Formal analysis, Software. **Patricia Melin**: Methodology, Software, Visualization, Project administration, Writing – review & editing, Funding acquisition.

**Declaration of competing interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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