Neurofuzzy models to automate the grading of old-age depression

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Abstract: Manual grading of depression is sometimes difficult due to the subjective signs-symptoms. The aim of this paper is to automate the process of depression grading using a neurofuzzy model (NFM). Two hundred and seventy real-world depression cases are considered in this work. Each case has seven symptoms, which are obtained according to DSM-IV-TR. Each case is graded as ‘mild’ or ‘moderate’. However, in practice, the boundaries of ‘mild’ and ‘moderate’ grading are fuzzy in nature. The paper attempts to solve this fuzzy overlapping zone of these grades. To reduce the number of symptoms, significantly correlated symptoms are mined using a paired t-test. Then, two NFMs have been developed. NFM-1 has been developed with all seven symptoms, while only significantly correlated symptoms have been used to construct the NFM-2 model. Two fuzzy membership functions, such as triangular membership function (TRMF) and Gaussian membership function (GMF) have been considered to note with which better fuzzification could be achieved. The paper concludes that NFM-1 with GMF is the best model with average predicting accuracy of 94.4% and robustness.

Keywords: depression, symptoms, diagnoses, neural-fuzzy model, sensitivity test

1. Introduction

Depression is described as the mental state where the subjects lose hope of life, remain isolated from the society, do not enjoy the events those were enjoyable in the past, feeling guilty or worthless and so forth. Studies have shown that 5–10% of the population at any given time is suffering from detectable depression and they require psychiatric management (WHO, http://www.searo.who.int/en/section1174/section1199/section1567_6741.htm), which is indeed an alarming situation. Currently, 30% of the global population is affected by depression (WHO, http://www.searo.who.int/en/section1174/section1199/section1567_6741.htm) and more interestingly it is showing an increasing trend among teenagers (Swartz et al., 2007) and children (Silberg et al., 2010). The most ominous outcome of depression is suicide (Holmes et al., 2007; Chattopadhyay & Daneshgar, 2011) and hence, depression needs urgent medical attention.

Old age or geriatric depression presents with all symptoms of depression at an older age, that is, beyond 50 years. It is quite uncommon compared to the number of reported cases between 18 and 45 years of age (Molyneux et al., 2008). Less reporting of old-age depressions may be due to the fact that unlike in other age groups, it is much overlooked and uncared for (Molyneux et al., 2008). Reactorony depression is the most common form of depression in old age (Bierman et al., 2007). Some common causes of such ‘reaction’ are loss of spouse/partner (Nithil & Martikainen, 2008), changes in the lifestyles (Roshanaei-Moghaddam et al., 2009), lack of coping to the stressful surroundings (Diamantopoulou & Papaioannou, 2007), unemployment/retirement (Lee & Smith, 2009) and several others.

Screening old-age depression is the foremost task to prevent the occurrences of several ominous consequences, such as suicide. Nevertheless, this is a much more complex process. The key reason is that the onset of depression is often unnoticed (Corruble et al., 2008). It leads to late screening and consequently delays the start of treatment. Another important reason lies in its subjective clinical presentation. Studies have revealed that like several other mental illnesses, depression present differently among the subjects and does not follow any particular pattern. The third cause lies with the medical doctors those perceive these symptoms according to their individual knowledge and logic, which varies from one doctor to another. As a result, often depression remains grossly ‘undiagnosed’, ‘under-diagnosed’ or ‘over-diagnosed’.

There are several depression-rating tools to study old-age depression (Beck et al., 1961; Zung, 1965). Screening tools mandate personal interviews. The answers given by the subjects are manually interpreted. It might inject bias in making the final diagnoses. This issue can be better dealt with intelligent computer algorithms, especially with soft computing techniques, although traditional mathematical methods have also been tried successfully (Chattopadhyay, 2012a; Chattopadhyay & Panda, 2012). Soft computing techniques handle uncertainty, non-linearity, and qualitative inputs encountered in mental health data better when compared to the traditional techniques. Fuzzy sets and fuzzy logic could better handle linguistic terms. It mimics the way human reasons. On the other hand, parallel processing for yielding speed in decision making, optimization to confer accuracy, learning and adaptation can be achieved with artificial neural network. It may be worth noting that individually these techniques have several demerits, which could be minimized or avoided if these are used in a complementary way. This is the basic principle behind the development of hybrid tools. Some
popular hybrid techniques consist of various combinations of neural network and fuzzy logic, neural network and genetic algorithm, fuzzy logic and genetic algorithm and so forth. The remaining portion of the paper is structured as follows. Related works are presented in Section 2. Section 3 details the materials and methods. Experiments and the related results are described in Section 4. Finally, Section 5 concludes the paper.

2. Related works

The suitability of soft computing techniques to handle much subjective neuropsychiatry data has been examined by several researchers since decades. The key interest is developing a case-based reasoning system (CRS). CRS mostly work by classifying illnesses by learning the exemplary patterns or cases under supervision (Chattopadhyay et al., 2011a).

In soft computing, ‘fuzzy sets’ have been used for the classification of depression using Beck’s Depression Inventory-II (Yu & Lin, 2008). The respective severity has been clustered with fuzzy C-means (FCM) (which is a soft clustering method) and K-means classification (which is a hard clustering method). The authors have concluded that FCM outperforms K-means technique.

The concept has been used further. Such as, attempts have been made to screen and grade seven different psychotic disorders (including depression) using ‘fuzzy clustering-to-controller’ technique (Chattopadhyay et al., 2007, 2008, 2009, 2010). In these work, ‘Brief Psychiatric Rating Tool’ has been used to capture symptoms of the respective disorders. The data are then modelled statistically with ‘Plackett-Burman Design of Experiments’ to avoid data dimensional complexity. Using multiple linear regressions, significant features or symptoms are obtained. Two fuzzy clustering techniques, such as FCM and entropy-based fuzzy clustering (with its extensions) are used to extract the information of the cluster centre. Because the cluster centres are the most useful representative information of the respective clusters, they are fed to the Sugeno type fuzzy controllers as the rule base. Finally, the inferences made by the controllers are fine tuned by a ‘Binary Coded Genetic Algorithm’. The study observes that the clustering-to-controller technique is useful in predicting neuropsychiatric disorders accurately and the controller obtained with FCM algorithm is more accurate than that of the controller, developed with entropy-based fuzzy clustering algorithm.

In another study, ‘fuzzy behaviour’ has been used in diagnosing Premenstrual syndrome (PMS), which is a type of dysphoria where depression is a predominant feature. Using the real-world data, a mathematical model has been developed. The heart of this model is a hierarchical tree induction using the principle of ‘information gain’, which guides the tree-splitting procedure. The feature with the highest ‘gain’ splits first. Fuzzy rules have been generated with the best features, obtained according to the ‘gain’ measure. Based on the firing strength of the rules, the PMS cases are classified (Chattopadhyay & Acharya, 2012).

A fuzzy-genetic algorithm model has been developed to analyze MRI signals for grading the severity of depression in a numeric form (Qing et al., 2010). The Hamiltonian scale (Hamilton, 1960) has been used for the rating function. The study concludes that the developed hybrid model is suitable to track recovery from depressions and it has been corroborated by analyzing the MRI signals.

Fuzzy clustering models, such as FCM and fuzzy K-nearest neighbourhood (F-KNN) have also been developed in the grading of adult depression (Chattopadhyay, 2012a). In this study, three distance measures such as Euclidean, Manhattan and Cosine have been investigated to obtain the best cluster. A special parameter called ‘cluster fuzziness’ has been set with careful parametric study to obtain the best clusters of desired numbers. The study finds that FCM gives better accuracy in the grading of depression.

Imprecision in the assessment of depression has been studied with a fuzzy-semiotic framework (Kwiatkowska et al., 2009). The authors used fuzzy logic to quantitatively represent the imprecision encountered during the measurement. Semiotic approach, on the other hand, represents the qualitative imprecision of the concept. For capturing the information, a self-administered questionnaire has been used. It has been observed that the framework has been extremely useful. Based on the observations, the researchers propose that such a framework could be extended as a full-fledged Clinical Decision Support System.

‘Neural networks’ (supervised as well as unsupervised) have also been tried to classify the grades of depression automatically using the signs and symptoms (Chattopadhyay et al., 2011a). The objective of this study is to clearly demarcate the grades of depression as ‘mild’, ‘moderate’ and ‘severe’ instead of the conventional way of grading, such as ‘mild-to-moderate’ and ‘moderate-to-severe’. The average accuracy of prediction is 89%. As an extension of this work, a self-organizing map (SOM) has been used to facilitate unsupervised learning. The reason behind this approach is that supervised training might be biased. With SOM, the average accuracy is improved to 96% (Chattopadhyay et al., 2011a).

In another study, a Multilayer Feed forward Neural Net (MLFN) has been developed to optimize the treatment of depression, which is conventionally done by trial and error method (Lin et al., 2010). The objective of the study is to investigate the effects of antidepressive drugs on the genomic status of the subjects. To accomplish the task, an MLFN-based predictive model has been developed using the (1) genetic information, such as single nucleotide polymorphism (SNP), (2) age of the subjects, (3) symptomatic load, measured by Hamilton’s score and (4) class of antidepressant medications, used. The results show that such an MLFN model is suitable to investigate the effects of drugs on the genomic status and hence could be useful in pharmacogenomic studies.

Neural networks have also been used to investigate the correlations between suicide attempts and the overall self-harms in Taiwanese soldiers (Tai & Chiu, 2007). The network has been tuned with a radial basis function (RBF) and it is found that the trained model can accurately establish such a correlation with 86% specificity. RBF net has also been used to develop an expert system for screening depression (Suhasini et al., 2011). The system uses backpropagation algorithm to extract significant features. The system can accurately (98.75%) screen depression.
Now, from these studies the following research scopes are identified:

1. Interfacing ‘old-age’ depression (i.e. the neuropsychiatric field) with Soft computing techniques.
2. Exploring the behaviour of the clinical data according to the size of symptoms (i.e. the dimension of the data matrix).
3. Choosing appropriate fuzzy membership function distributions to handle the fuzzification phase of a fuzzy controller.
4. Finally, testing the sensitivity of the neurofuzzy controllers by varying the test data by 1, 5, 10 and 15%, randomly. This is an important task to assess the goodness (robustness) of any controller.

3. Materials and method

This section describes various processes and techniques are adopted in the ambit of this paper.

1. Data collection.
2. Data analysis and its reliability check.
3. Neural-fuzzy model (NFM) development and the performance analyses.

In this work, all experiments have been performed with Matlab-7.8 (http://www.mathworks.in) on a P-IV (dual core) computer.

3.1. Data collection

Anonymous data of real-world depression cases have been obtained from hospital sources in Eastern India. It took 2 years to complete the collection. During data collection, five experienced psychiatrists and two psychologists (those are the domain experts) took part. Information of total 270 depression cases (anonymous) is obtained from the paper-based history sheets. Each case has seven clinical symptoms, for that is, ‘sadness’ (S), ‘fatigue’ (F), ‘abandoning’ (AB), ‘social withdrawal’ (SW), ‘weight loss’ (WL), ‘sleep disturbance’ (SD) and ‘alcoholism’ (AL), according to Diagnostic and Statistical Manual (fourth edition, text revision) DSM-IV-TR (American Psychiatric Association, 2000) are considered for describing each case. The corresponding severity of each case is either ‘mild’ or ‘moderate’, assigned by the experts. Table 1 shows the data summary.

As mentioned, such diagnoses are made according to doctors’ perceptions and clinical knowledge, and hence they might be biased. It is assumed that the boundaries of ‘mild’ and ‘moderate’ depression are ill defined and hence fuzzy.

3.2. Data analysis and reliability check

The data has been tested for (1) missing values, (ii) redundancies and (3) clerical errors. Further, the data have been tested for measuring the central tendency and distribution, symptom-wise. Mean (MN), standard (ST) deviations, skewness (SK), kurtosis (K) and p-values (based on paired t-test with CI: 95%) are computed. The reliability of the data has been checked by measuring Cronbach’s alpha (α) (Cronbach, 1951), which is expressed by equation (1).

\[
\alpha = \frac{N \times \bar{c}}{\bar{v} + (N - 1) \times \bar{c}}
\]

Here, ‘N’ denotes the number of cases; ‘\(\bar{v}\)’ and ‘\(\bar{c}\)’ are ‘average variance’ and ‘average of co-variance’, respectively. With this data set, a predictive model has been developed using neural network and fuzzy logic as a hybrid, which is discussed next.

3.3. Neural-fuzzy modelling (NFM)

It is a hybrid of neural net architecture and the concept of fuzzy set and fuzzy logic. Here, fuzzy operations are carried out with six neural layers (refer to Figure 1).

In Figure 1, ‘X’ to ‘\(X_m\)’ denote the inputs (i.e. depression cases, each having seven symptoms [0,1]) and ‘A’ denotes the ‘grade’ of each input, which is either ‘mild’ or ‘moderate’ in these cases. This is layer 1 (i.e. the input layer). In real-world scenarios, often the input passes through the overlapping area of ‘mild’ and ‘moderate’ grades (e.g. mild-to-moderate depression) and creates clinical confusion. To handle this issue, each grade is represented with two fuzzy sets (see Figures 2 and 3) and the membership (\(\mu\)) of the input with each fuzzy set is computed to note the degree of belongingness of each case with the grades. In this work, triangular and Gaussian membership functions are considered (see Figures 2 and 3). The neural layer where \(\mu\) values are computed is the second neural layer, known as the ‘fuzzification layer’.

Products of the membership grades (i.e. firing strengths of the rules) are then computed according to the fired rules (IF-THEN) in layer 3, which is also known as ‘product layer’. Normalized products (i.e. relative firing strengths) are computed in layer 4; defuzzification is performed in layer 5 by multiplying the output (as the polynomial function of the inputs) with relative firing strength. Finally, the crisp output is obtained in layer 6. The calculated output is then compared with the target output and the ‘error in prediction’ is obtained.

The advantage of such a hybrid is that the inference drawn by the fuzzy logic controller could be fine tuned by a back-propagation method, otherwise a fuzzy logic controller only infers and cannot optimize the inference further. In this study, for each case, there is either a ‘mild’ or ‘moderate’ class label. Now, the issue lies in deciding their boundaries, which is critical for grading depression and accordingly planning the treatment. It is important to note that ‘mild’ and ‘moderate’

<table>
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<tr>
<th>Table 1: Data summary</th>
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<tr>
<td><strong>Parameter</strong></td>
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<tr>
<td>1. No. of cases grade wise</td>
</tr>
<tr>
<td>2. No. of symptoms</td>
</tr>
<tr>
<td>3. Symptom load</td>
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<tr>
<td>4. Severity/grade</td>
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<td>5. Severity range</td>
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<tr>
<td>6. Males</td>
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<tr>
<td>7. Females</td>
</tr>
<tr>
<td>8. Age group</td>
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<tr>
<td>9. Duration of current illness</td>
</tr>
<tr>
<td>10. Duration of illness from its onset</td>
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<tr>
<td>11. Treatment history</td>
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Figure 1: The proposed neurofuzzy model.

are the qualitative terms, popularly used by the medical doctors. In real-world scenarios, it is impractical to assess these terms into binary (0, 1); because there may be transitional cases from mild to moderate and vice versa, which are seen in the clinical practice. The reasons behind such transitions could be (1) the effect of medications, (ii) the changes in the course of illness and (iii) the differences in perceiving the loads of symptoms and the grade of the disease by the medical doctors. Hence, instead of choosing a perceptron model or a fuzzy-based controller, a NFM has been chosen in this work. As mentioned in Section 2, a multilayer perceptron-based controller without fuzzy approach has already been designed by the author (Chattopadhyay & Acharya, 2012) and it could diagnose ‘moderate’ cases with only 77% accuracy. The possible reason could be that the perceptron-based controller was unable to handle the fuzziness within the features of the ‘moderate’ cases, which this paper attempts to address.

According to the domain experts’ (i.e. the medical doctors) opinion, the range of ‘mild’ depression is set as 0.1–0.6. The range of ‘moderate’ depression is 0.5–0.8. It is important to note that range setting is a double blind process to avoid human bias. Hence, the overlapping portion lies in 0.5–0.6, which is actually encountered in the clinical practice. These ranges are mapped with two most commonly used membership functions, such as triangular membership function (TRMF) and Gaussian membership function (GMF) to note that one works better for this data set. Figures 2 and 3 show the TRMF and GMF with the ranges of ‘mild’ and ‘moderate’ grade of depression. The fuzzy zones, that is, the

Figure 2: Triangular membership function (TRMF).

Figure 3: Gaussian membership function (GMF).
overlapping portion of ‘mild’ and ‘moderate’ grades are identified. This is an uncertain zone of decision making if an input (i.e. ‘x’) passes through it; because the input neither discretely fall inside the ‘mild’ nor in the ‘moderate’ class. Such uncertainty may cause biasness among the doctors. According to their individual experiences and perceptions, they label a case as ‘mild’ or ‘moderate’. When ‘mild’ case is diagnosed as ‘moderate’ it leads to ‘over’ diagnosis and vice versa. Sometimes, the diagnosis is made as ‘mild-to-moderate’, which is confusing to decide on a management plan. Such complexities are handled by fuzzy sets. It is important to note that in fuzzy sets, the membership functions are used to fuzzify the input data. During fuzzification the data are actually handled in the fuzzy environment, which largely influences the output obtained by defuzzification. Hence, choosing an appropriate membership function may reduce the amount of error during defuzzification.

4. Results and discussions

All the experiments in this work have been performed on Matlab 7.8 using neural network graphic user interface. Tables 4 and 5 give the detail information about the training and testing processes, respectively.

4.1. Data analysis

At first, the data distribution and the central tendency has been tested. The result is shown in Table 2, where columns represent seven symptoms, described in Section 3.1. The rows are ‘MN’, ‘ST’, ‘SK’ and ‘K’ denoting mean, standard deviation, skewness, and Kurtosis, respectively, for each symptom. In statistics and probability theory, skewness measures the asymmetry of probability distribution of any real-valued random variable. A positive skew indicates that the distribution tapers at the right side, that is, the mass of the distribution is concentrated on the left of the distribution. This is reverse for the negative skewness. Kurtosis, on the other hand measures the outliers within the data set.

Table 2 shows that ‘AB’, ‘SW’ and ‘AL’ have a negative skewness and the remaining symptoms are positively skewed. Hence, overall, the data show a moderate degree of asymmetry, which is often encountered in case of real-world data. No asymmetry means that the skewness values must be close to ‘0’, which is certainly not a case here. As the Kurtosis (K) of none of these symptoms is over 3.0, it could be stated that there is no outlier within the data set.

In addition to the distribution and central tendency, reliability of the data has also been tested using Cronbach’s α test. The measured ‘α’ value for this data set is 0.81, which is higher than the stipulated threshold 0.7 (Nunnally, 1978). Hence, the data used in this study could be considered as reliable and internally consistent for the experiment.

4.2. Neurofuzzy model (NFM)

Two NFMs have been developed – the first model (i.e. NFM-1) is designed with all seven symptoms, while NFM-2 is a modified version of NFM-1, where only significant symptoms, such as ‘AB’ (i.e. abandoning) and ‘AL’ (i.e. alcoholism) are considered. Each symptom is expressed into two qualitative terms such as ‘mild’ and ‘moderate’. It is assumed that the boundaries of ‘mild’ and ‘moderate’ grades are indistinct, which is the research challenge here. To start from the scratch, the ranges of values in ‘mild’ and ‘moderate’ cases have arbitrarily been set by the medical doctors using their domain knowledge. Accordingly, medical doctors are asked to give a range of mildness and moderateness. The range that has been used in the experiment is chosen based on the range that has least squared error (LSE).

With seven symptoms, the numbers of possible rules are $2^7$, that is, 128 in case of NFM-1. In case of NFM-2, the number of rules is $2^4$ that is, 16. The rule base is created automatically by Matlab using all possible ‘IF-THEN’ combinations. The rule consequent is defined as a polynomial function of the symptoms [0, 1], as seen in Sugeno’s type of fuzzy controller. The polynomial coefficients and the constants are computed on Matlab during the training run. Constants are nothing but the half-width values [0,1] of mild and moderate fuzzy sets, that is, 0.35 and 0.65, respectively, where the degrees of the memberships are maximum, that is, 1.0 (refer to Figures 2 and 3). On the other hand, coefficients are the input values [0, 1]. The best coefficients and constants are then used while testing the performance of the control. It is important to note that the best learning rate and step length are obtained with parametric studies. These optimized values are then used during backpropagation, by which the membership values are updated iteratively so that the LSE is generated.

Seventy percent of the data are fed into the controller for training and the remaining 30% of the data are used for testing the performances of the controllers, after a 10-fold cross-validation in each time. At first, TRMF is considered. Then GMF has been tried to see whether there is any improvement in prediction. The performances during training with TRMF and GMF are shown in Tables 4 and 5, respectively. It is interesting to note that while testing, the LSE is the lowest in case of NMF-1 with GMF, that is, 5.8% compared to 6.11% with TRMF. NMF-2 gives higher LSEs in both TRMF and GMF. Therefore, this type of NMF model has not been considered further in this study, except for the
Table 4: NFM ‘training’ and test results [triangular membership function (TRMF)]

<table>
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<tr>
<th></th>
<th>NFM-1</th>
<th>NFM-2</th>
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<tbody>
<tr>
<td>No. of nodes</td>
<td>294</td>
<td>55</td>
</tr>
<tr>
<td>No. of linear parameters</td>
<td>128</td>
<td>16</td>
</tr>
<tr>
<td>No. of non-linear parameters</td>
<td>42</td>
<td>24</td>
</tr>
<tr>
<td>Total no. of parameters</td>
<td>170</td>
<td>40</td>
</tr>
<tr>
<td>No. of training data pairs</td>
<td>189</td>
<td>189</td>
</tr>
<tr>
<td>No. of fuzzy rules</td>
<td>128</td>
<td>16</td>
</tr>
<tr>
<td>Least squared error (LSE):</td>
<td>6.11%</td>
<td>21.06%</td>
</tr>
<tr>
<td>Training and test</td>
<td>5.91%</td>
<td>20.89%</td>
</tr>
</tbody>
</table>

4.3. Testing the sensitivity of the developed expert system

It is desired that an expert system should not be hypersensitive to the changes made in the input data. The performances of the NMF models are therefore tested by varying the test data by 1, 5, 10 and 15% and the respective LSEs are computed. ‘LSE vs % of data change’ plots are obtained for both TRMF and GMF (see Figures 5 and 6, respectively). From the plots, it could be noted that with the changed values, LSEs are increased by 13% and 3% in NFM-1 and NFM-2, respectively, for the TRMF. On the other hand, the LSE values are increased by 10% and 1% with GMF. Therefore, with GMF, the controllers are less sensitive to the changes made in the input data. It is further noted that, NFM-1 is less hypersensitive than NFM-2 in case of both TRMF and GMF. Thus, NFM-1 with GMF is the best model.

5. Conclusions

Appropriate grading of old-age depression is important for catering better healthcare. Variation in the clinical perceptions and experience is still an issue for diagnosing the grades...
distinctly. Hence, automating the diagnosis process might be helpful. In this paper, two NFMs have been developed. Each has been tested with TRMF and GMF to handle the fuzzification phase of the controller. It is observed that with GMF better accuracies in prediction are obtained, compared to TRMF. Two possible reasons could be that (1) it is able to render a smooth, continuously differentiable hypersurfaces of fuzzy model and hence (2) it is able to facilitate the theoretical analysis of fuzzy systems where the environment is non-linear and complex. In this study, NFM-1 with GMF produces maximum accuracy of 94.4% in predicting the depression grades. The author proposes that, in future, such a model can be extended into a full-fledged expert system for the real-life use after carefully designed experiments and appropriate standardization.

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