Accuracy Improvement of Neural Networks Through Self-Organizing-Maps over Training Datasets

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Abstract. Although it is not a novel topic, pattern recognition has become very popular and relevant in the last years. Different classification systems like neural networks, support vector machines or even complex statistical methods have been used for this purpose. Several works have used these systems to classify animal behavior, mainly in an offline way. Their main problem is usually the data pre-processing step, because the better input data are, the higher may be the accuracy of the classification system. In previous papers by the authors an embedded implementation of a neural network was deployed on a portable device that was placed on animals. This approach allows the classification to be done online and in real time. This is one of the aims of the research project MINERVA, which is focused on monitoring wildlife in Doñana National Park using low power devices. Many difficulties were faced when pre-processing methods quality needed to be evaluated. In this work, a novel pre-processing evaluation system based on self-organizing maps (SOM) to measure the quality of the neural network training dataset is presented. The paper is focused on a three different horse gaits classification study. Preliminary results show that a better SOM output map matches with the embedded ANN classification hit improvement.

Keywords: Self-organizing map · Artificial neural network · Feedforward neural network · Pattern recognition · Locomotion gaits

1 The MINERVA Project

In the last years, the monitoring of wildlife has become a very relevant topic thanks to concepts like the Internet of Things (IoT) and technologies like wireless sensor networks (WSN). Several studies have focused on investigating the

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best way to gather information about animal patterns using embedded devices that are placed on animals [1–5]. This task is very important when it comes to understand things like the interaction between animals, their survival or even their nutrition habits. Changes in weather, flora or the introduction of non-native species could also affect these activities, making the monitoring of animal motion patterns a very interesting task.

A 2.4-GHz ZigBee-based mobile ad hoc wireless sensor network is presented in [6] to collect motion information from sheep and send it to a base station, which will later be classified into five different behaviors (grazing, lying down, walking, standing and others) using a multilayer perceptron (MLP) artificial neural network (ANN). The accuracy rate of the network is 76.2% without any applied preprocessing method.

MINERVA is a research project whose aim is to study and classify wildlife behavior inside Doñana National Park. The tracking and classification systems that are being used nowadays in the park obtain positional information between two and five times a day (to reduce power consumption) using a GPS and transmit it via GSM. However, biologists need more information to be able to recognize animal patterns. In previous work by the authors, this problem is solved by doing the classification step inside of the collar that is placed on the animals using an embedded implementation of an Artificial Neural Network (ANN) [4] instead of sending the raw sensor information to the database that is later studied by the biologists. This way, several sensors monitoring are carried out, but only the classification result is sent to a base station which later uploads it to a remote database. Hence, less transmissions are needed, which is the activity that consumes most battery power (more than 80% as presented in [7]). Previous studies have used this approach to classify between three horse gaits (standing, walking and trotting) [8], which used different preprocessing techniques applied to the raw data to obtain a better classification result in the embedded ANN. In [4,5] Kalman filter is applied to the input data, obtaining a 81.01% accuracy result. Moreover, in [3], Overall Dynamic Body Acceleration (ODBA) and variance is applied to the same data using different window lengths, achieving up to a 90.3% accuracy. However, to test which preprocessing would have a better accuracy result of the ANN, the whole trial and error method needs to be done. In our case, this task is hard and expensive (in time), so a tool or mechanism to test how good are the preprocessing methods is needed.

In this work, the authors present a novel NN-based mechanism to test the quality of the preprocessed information before having to test it using it as input to the classifier. Self-organizing Maps (SOM), which are a type of ANN, are used to visually show how good the input data is, and how the sensor data differs between each of the classes that want to be classified. This way, if the preprocessing is able to properly sparse the data between each of the classes, the ANN would then have it easier to classify the input information, achieving a better accuracy result. SOMs are usually used for classifying samples which have a features set with different values. The result is a map where samples with similar values are close, and samples with different values are separated, thus appearing sample clusters. The most popular example using SOM is the Fisher's Iris data set [9] problem, where three species of Iris flower have to be classified taking into account some features like sepal length, sepal width, petal length and petal width. In [10], authors using the SOM for processing the characterization of movement patterns of athletes, taking several training session parameters. And in [11], an unsupervised acoustic classification of bird species was done extracting first some features by spectral analysis and using them to classify the species using a SOM. In both cases, several parameters had been extracted in order to be used as SOM input applying complex preprocessing methods. The rest of the paper is structured as follows: Sect. 2 describes the collar device used to gather information from animals, and how this data is obtained. Then, Sect. 3 presents different preprocessing techniques to improve the information that can be extracted from the sensors. Section 4 describes the experiments that have been carried out in this work, as well as the results obtained. At the end, Sect. 5 presents the conclusions of this work.

2 Collecting Sensory Information Using a Portable Collar Device

The collar (Fig. 1) collects information from the animal that carries it by using different sensors. It has a MinIMU9V2 inertial measurement unit (IMU), which consists of an LSM303DLHC 3-axis accelerometer, an L3GD20 3-axis gyroscope and a 3-axis magnetometer. Each of these sensors have 12-bits resolution for a more precise data acquisition. Along with the IMU, a GPS is also used, which provides location and time information. The collar has a 2.4 GHz ZigBee-based radio module, which is an open global standard of the IEEE 802.15.4 MAC/PHY [12], to send the obtained information. The collar carries a MicroSD card to store the sensor's information when the animal is outside of the coverage range of the WSN.

The data that is used on this article has been collected from semi-wild horses and different seasons. A total of 30000 samples were obtained during visits to Doñana's National Park from different horses. This data corresponds to three gaits: standing, walking and trotting. Several methods have been used in the literature to classify this kind of locomotion information: Convolutional Neural Networks, Support Vector Machines, statistical methods, etc. High accuracy results have been achieved, as it was presented in Sect. 1. However, these kind of algorithms have a high computational cost, which leads to a high power consumption.

The main aim of the collar is to classify the animal behavior (between three different gait patterns in this work) using the information obtained from the IMU as an input to a feed-forward Artificial Neural Network (ANN) implemented on the collar's microcontroller unit (MCU). To implement an ANN in the collar an open source neural network library called Fast Artificial Neural Network (FANN) [13] has been used. This library allows to implement multilayer ANNs in C programming language in an easy and quick way.

As in MINERVA project the application needs to be focused on low-power consumption devices (capturing an animal to replace its collar is very expensive

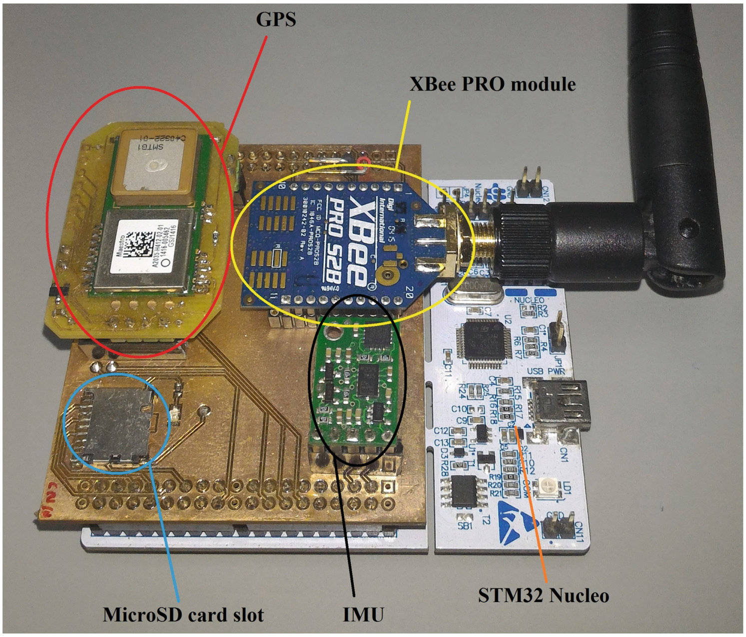


Fig. 1. Collar device prototype. Several sensors are necessary to monitor the activity and position of the animal. The XBee module allows to send the collected information to the base station that is placed on the park.

and difficult), an MCU with no Floating Point Unit (FPU) is used. Hence, for this purpose, the FANN library was modified to use fixed point numbers. Processing the sensor's information in the collar allow us to only send the classification result to the base station instead of all the raw data gathered from them, reducing the number of transmissions (as it was studied in [14], transmissions have a very high power consumption compared to the ANN operations) and the length of the packets transmitted, and letting us to know the animal behavior in real time [4].

3 Collected Information Processing and Analysis

Processing the sensor information after it has been collected is a common task. This way, the noise that data may have can be reduced, obtaining a better signal, or even extracting information that could be hidden in the raw data.

Data signals provided by the accelerometer vary between –2g and 2g in this case. The horse gaits information is included in these signals, and the main challenge is to get these features by performing some math operations to transform the samples, in order to provide a better input to the ANN implemented in the collar.

For this purpose, the authors have carried out several experiments in which different data processing methods were applied. Kalman filter, variance, among others, were calculated and tested using them as an input to a feedforward ANN. However, we did not have any parameter or index that showed us how good the preprocessing step was. Until now, the quality of the processing performed to the input dataset (understanding quality as how good this data is) is evaluated by analyzing the output of the ANN and checking the confusion matrix to see how good the accuracy result is. In this work, we considered that it would be interesting to have a tool which helped us in this task, giving information about the quality of the preprocessing and the input dataset before testing it on the ANN.

Self-Organizing Maps (SOM) [15] is a type of ANN used to cluster input data into groups of similar patterns. Input patterns are compared to each cluster, and associated with the cluster it matches the best. The comparison is usually based on the square of the minimum Euclidean distance. When the best match is found, the associated cluster gets its weights and its neighboring units updated. Preprocessing methods used and carried out tests using SOM will be explained in detail in order to clarify our use of SOM.

3.1 Information Preprocessing

While the collar is working, it is continuously collecting data from the IMU sensors. This raw data generally has a lot of noise, but sometimes it can be used as it is, without any previous processing. The fact is that ANNs achieve a better classification result for a specific category when the information from it is distant from the input information of the rest of the classes. In this case, the problem was that, in our dataset, sensor values from different gaits are overlapped because of the accelerometer's range and the nature of the animal movement, as we can see in Fig. 2. So, even though the ANN output was acceptable (around 80.0%), the device needs to have more accuracy, since it will be active only a few hours a day to reduce power consumption. The first solution taken by authors was to implement the Kalman filter [16] in the collar. This method is commonly used by planes and drones, which provides information about the orientation of an object in a 3-dimensional space. Kalman filter uses raw data as input and returns three values: roll, pitch and yaw. Using this parameters a 95.0% of accuracy was achieved by the ANN, but power consumption was increased considerably, reducing the battery life of the collar. In addition, floating point operations (which require a FPU module) are needed to perform these calculations and, as it was presented in previous sections, low power consumption MCUs without FPU are needed in this project, making it a not viable solution.

In search of a simple solution, after several methods were studied, the variance of the raw data was calculated. In this case, since the device has to work in real time, this operation was performed using temporal windows of 1.3 s approximately (40 samples, having a 30.3 Hz sample frequency). When the buffer is full, the variance is calculated and used as input to the ANN. This way the MCU collects data during the enough amount of time to let us know the gait that the

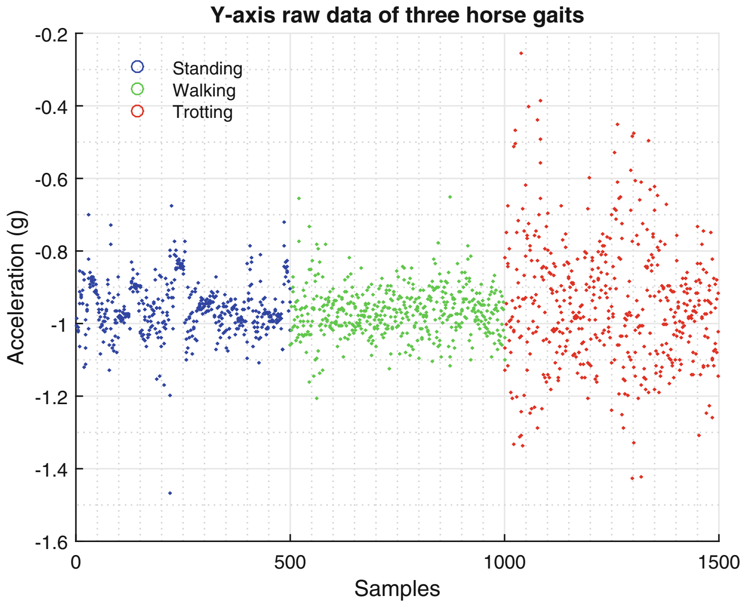


Fig. 2. Raw data subset from Y-axis of accelerometer. Three gaits are showed consecutively using different colors (5000 samples per gait). Most samples are located in the same range of values. (Color figure online)

horse is performing. Around 90.0% accuracy was achieved when calculating the variance of the input sensor information [3].

When variance data was shown against time (Fig. 3), it could be seen that some peaks from different gaits were overlapped between them. Therefore, in these cases, the ANN could probably give a wrong result when trying to classify the information. In order to avoid this situation, a window-length-based hull of maximum values was performed. This operation consists on detecting the maximum value of the samples contained in the window and maintaining that value until a greater peak is found or until the end of the window. This way, the ANN input data will be always the peaks of the signal, which are the best ones that represent the gait performed by the horse, except some cases in which an isolated peak is produced by an unusual movement of the horse.

3.2 Data Analysis Using Self-Organizing Maps

As it was presented previously, data from different gaits is frequently overlapped. This situation could lead the ANN to a wrong classification. Hence, it would be good to analyze the input dataset and know how the spacial distribution of samples is, to check if it is possible to differentiate the three gaits. In the optimum case, the information of each gait should be well separated in three different clusters. But the real case is that these signals are usually closer to each

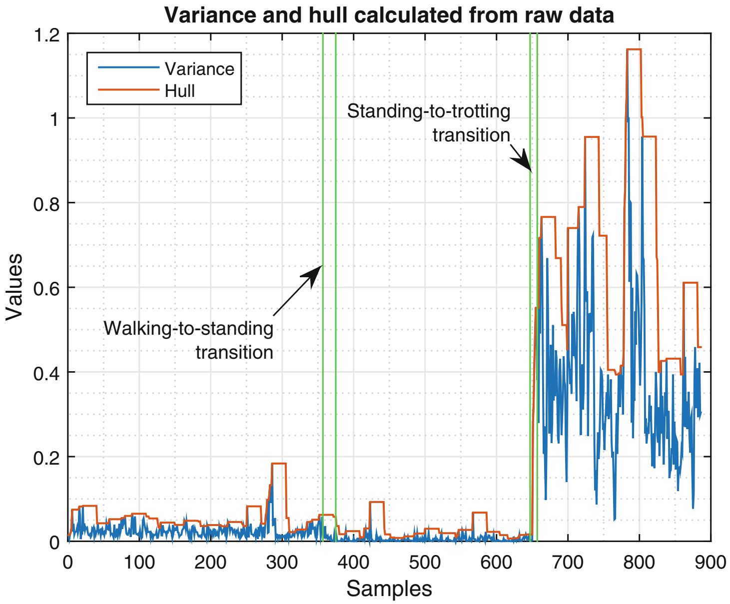


Fig. 3. Variance of the raw data from the Y-axis and hull of variance values. Two transition areas can be identified, which are delimited by vertical green lines. In this case, gaits are sorted as walking, standing and trotting. The number on samples was reduced due to window-based preprocessing method. (Color figure online)

other, even overlapped (due to the transitions between gaits and the nature of the horse movement).

For this reason, SOMs were used to analyze the dataset, since they are able to show how good the samples are distributed and point out the existing data clusters, which in this case they will correspond to the gaits performed by horse. Thus, the better differentiated the data is, the better the SOM will be able to represent a map where the three gaits are perfectly distinguished. However, a bad SOM's output does not implies a bad result of the ANN, but it means that samples from a specific category are not well separated from the rest of them.

In addition, a SOM may help us understand the results obtained when using a classification system like a feed-forward neural network, statistical methods with thresholds, etc. The aim is to perform an appropriate sample processing in order to obtain a good SOM's output, and thus, a good accuracy on the classification with the ANN.

4 Offline Tests and Results

Several tests were performed using SOMs and applying the different preprocessing methods that were presented in previous sections. These tests were carried out offline, due to the fact that it makes no sense to implement a SOM in the collar's MCU and use it in real time. MATLAB has several toolboxes that allow to train and test different kinds of ANNs. Among them, Neural Network Clustering and Neural Network Pattern Recognition are mostly used to work with SOMs and feedforward neural networks, respectively.

For the Neural Network Clustering Toolbox, the input vector length was different on each case of study, depending on the dataset used (9-samples input vector for the raw data or 3-samples input vector for the variance and the hull). A two-dimensional map with size 8 (i.e. 8×8 neurons) was trained using this application. The default values of training parameters, like number of epochs and training algorithm, were used. The ANN architecture used to test the dataset consists of a hidden layer with 30 neurons and an output layer with 3 neurons (one per gait). The activation functions used were the sigmoid transfer function in the hidden layer and the softmax transfer function in the output layer. The NN was trained using the backpropagation algorithm, and it was used the same architecture for all performed tests.

Three different tests were carried out, using three datasets (raw, variance and hull) in which the data was processed using the methods explained in previous sections. Both confusion matrix and SOM's output show the results obtained in each test, which can be seen below:

4.1 Raw Data

The raw data has the information from the 3 axes of the accelerometer, gyroscope and magnetometer. Therefore, nine neurons are needed in the input layer of the NN and the input vector of the SOM. Much noise is found in the signals, so it is hard to recognize patterns with a high accuracy.

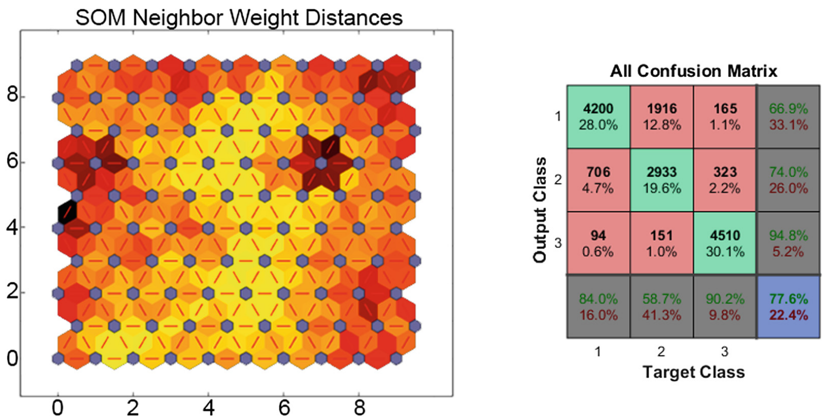
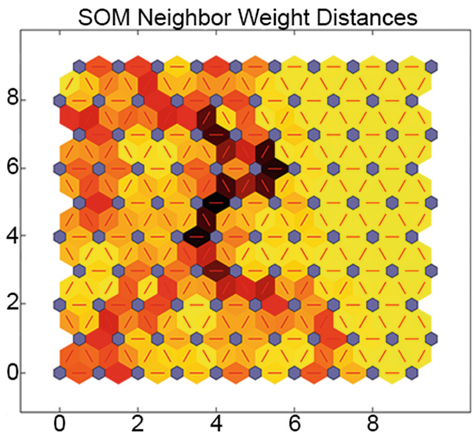


Fig. 4. SOM's output (left) and confusion matrix (right) using raw data. Target classes are corresponded with: 1-walking, 2-standing, 3-trotting.

Figure 4 left shows the SOM's output, where lighter colors respresents neurons with similar values and darker colors represent neurons with different values. In the other hand, right side of the picture shows the confusion matrix, where bottom row and right columns are the average per clases and botom-right cell is the hit averate. The hit average obtained by the ANN is 77.6.

4.2 Variance

To calculate the variance, only the three axes of the accelerometer were taken into account, because it is the sensor which provides more information about the animal locomotion patterns [5]. The variance was calculated using a 1.3 s length (40 samples) window size, which is approximately the time that the horse takes to perform a full period of any of the gaits studied in this work.



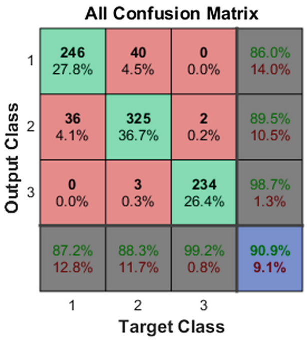


Fig. 5. SOM's output and confusion matrix using the variance data calculated from raw samples. Target classes are corresponded with: 1-walking, 2-standing, 3-trotting.

After the samples were processed, the data obtained seems to be clearer than raw data since the SOM's output (Fig. 5) shows two well differentiated areas, which could correspond to trotting and standing/walking because those last two gaits are hard to classify, as can be seen in Fig. 2 in Sect. 3.1. In the area corresponding to standing and walking gaits, the difference is not easy to be distinguished. This situation does not happen with trotting, because samples have higher values and transitions to or from this gait are more sudden than the others, so they are well separated from the rest.

This improvement seen in the SOM's output is reflected in an increase of the hit average achieved by the ANN, where a 90.9% of accuracy was obtained using this process. Furthermore, an improvement in the hit average between both standing and walking was obtained.

4.3 Hull

Using this approach, the authors tried to avoid the problem of samples similarity. The input data was the same variance values that were calculated previously, which have now been processed with a hull algorithm using a slice of 20 samples.

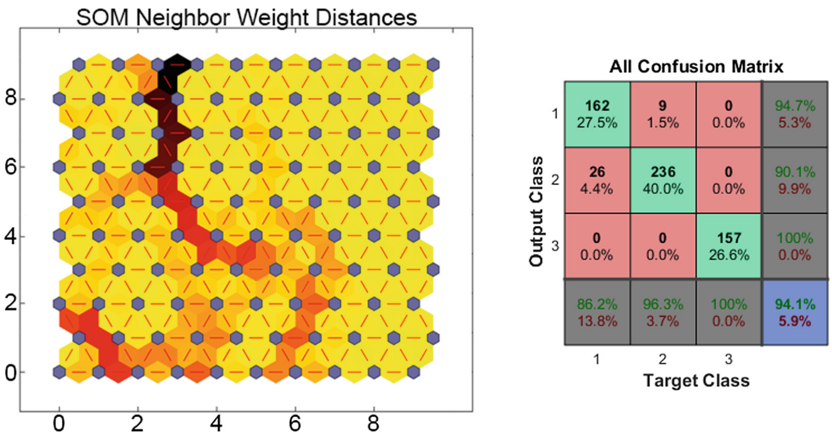


Fig. 6. SOM's output and confusion matrix using the hull data calculated from variance values. Target classes are corresponded with: 1-walking, 2-standing, 3-trotting.

Now, the output from the SOM shows three different areas clearly, although there is an area that is not perfectly differentiated as the others (Fig. 6). This situation corresponds to standing and walking gaits, since the movement of the horse's head (where the collar is placed) is almost the same in both cases. The improvement showed in the SOM's output was directly confirmed when the ANN was tested using the calculated values. The hit accuracy obtained with the ANN was 94.1%.

The hull algorithm can be done in real time, due to the fact that the computational cost needed to calculate it is very low. This solution increases the previous one by a 3%, taking only the maximum value in each time slice.

An improvement in walking prediction is a hard task, since more complex operations are needed to extract more information from the samples. However, with this preprocessing technique, we can consider that the collar device is reliable enough to provide information about animal gaits.

5 Conclusions

In this paper, the authors have presented a novel mechanism based on SOMs to measure the quality of the input dataset before training and feeding a NN with it. This way, the user is able to know how good the information from the different classes that are contained in the dataset is, and how much they differ from each other. The more separated the information from different classes is, the better accuracy will be achieved by the ANN when classifying samples. Hence, SOM is a useful tool for predicting how good the classification results will be before testing the ANN, to the fact that this process is hard and very expensive in terms of time and money.

In this context, three different experiments have been carried out where three horse gaits were studied, comparing the SOM output with the accuracy result achieved with a feedforward ANN. Both architectures have been trained and tested using MATLAB Neural Network Toolbox. The first experiment consisted on testing the ANN with the raw data obtained from IMU sensor. A 77.9% was achieved with this system; however, the SOM was not able to cluster the information in the three different classes. On the other hand, when the dataset was preprocessed using the hull algorithm, three different areas (clusters) could be seen or distinguished in the obtained map, which was not possible with the previous preprocessing methods. Using this processed dataset as input to the ANN improved the classification, achieving a 94.1% accuracy. Hence, this SOM application became useful for the authors. The hull method can be deployed into the collar to improve the accuracy of the horse gait classification system using the embedded ANN, which is able to obtain the same performance of MATLAB Neural Network Pattern Recognition toolbox [4].

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