# Assessing impacts of data volume and data set balance in using deep learning approach to human activity recognition

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***Abstract*—Over the past decade, deep learning developed rapidly and had significant impact on a variety of application domains. It has been applied to the field of human activity recognition to substitute for well-established analysis techniques that rely on handcrafted feature extraction and classification methods in recent years. However, less attentions have been paid to the influence of training data on recognition accuracy. In this paper, we assessed the influence factors of data volume and data balance in human activity recognition when using deep learning approaches. We evaluated the relationship between data volumes of training dataset and predict accuracy of deep learning algorithms. Given the impact of the data balance between activity categories on the recognition accuracy, we modified the SMOTE algorithm so that it can be applied to human activity recognition. Results show that when the data volume is small (<4M), the recognition accuracy increased quickly with the increase of the quantity of training data. However, the growth trend of recognition accuracy slows down when the data quantity reaches 4 million. Further increase the data volume does not significantly improve the activity recognition performance. So we can conclude that 4 million data volume can ensure a sufficient accuracy for human activity recognition. Meanwhile, the data set balance operation can not only improve the recognition accuracy of minority categories, but also helps to increase the overall accuracy.**

***Index Terms*—human activity recognition, deep learning, LSTM, CNN**

## I. Introduction

A new generation of smart phones is equipped with a variety of sensors which are used for meeting peoples growing demand of their own activities and health needs. These sensors include GPS sensors, audio sensors (i.e., microphones),image sensors (i.e., cameras), light sensors, temperature sensors, direction sensors (i.e., compasses) and acceleration sensors (i.e.,accelerometers). Because of the small size and enabling programmable expansion of those mobile devices, smartphones become an excellent platform for sensing. With these support, human activity recognition has emerged many applications, such as health system, anti-fall detection, traffic path planning and so on [1], [2]. For example, HealthAware system uses the acceleration sensor to monitor the users daily movement and remind the user to maintain a certain amount of exercise every day [3]. PerFallD system uses the acceleration sensor to detect the fall of the elderly and issue a real-time warning to other relevant users [4].

The history of human activity recognition based on smartphone can be traced back to the early 21st century. Five acceleration sensors had been fixed in the hip, wrist, arm, thigh and ankle to collect the user's activity data and identify 20 kinds of daily activities, the final results show that the sensor which was placed in thigh part achieved the best result [5]. Aarts RM et al [6] demonstrates that high accuracy can be achieved by relying solely on a single sensor, which greatly simplifies the test complexity of subsequent related experiments. Subsequent studies are intended to improve the recognition results from the algorithms or data standpoint. Jennifer R et al [7] uses the data of UCI HAR database to identify the human activities and obtain about 90% recognition accuracy by using decision tree and support vector machine. On their basis, Kadian Davis et al [8] increased the amount of data set and adopted the hybrid of Hidden Markov Models(HMM) and SVM (SVM-HMM) algorithm to improve recognition accuracy.

Over the past decade, deep learning represents the biggest trend in machine learning. It has had significant impact on a variety of application domains [9]. Because of its self-learning characteristics, many scientists have used it in the field of human activity recognition. Daniel Roggen [10] propose a generic deep framework for activity recognition based on convolutional and LSTM recurrent units. The breadth of this framework makes it highly recognizable for different databases. Yuqing Chen [11] used a single database to achieve the 93.5 recognition accuracy, which proves that CNN model has better prediction effect for less data volume. Unlike the previous CNN model, Sojeong Ha [12] uses the multi-time

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data of the acceleration and gyroscope and elevates the original 1-D network to 2-D network, thus increasing the recognition accuracy to 94.43%. Yuwen Chen [13] uses the LSTM model to train seven kinds of movements, which are up and down the stairs, sitting, standing, walking and running, and finally obtaining 95.1% recognition accuracy. It is suggested that LSTM is more suitable for identifying time series data than CNN. On the basis of this conclusion, Nils Y.Hammerla et al [14] studied the division of the data time window, which further improved the recognition accuracy.

Although the previous researches have achieved good accuracy in activity detection, there are few reports about the impact of the volume of training data on accuracy, as well as the relationship between data set category balance and recognition accuracy. Many reports are comparing the results of multiple database identification, but do not propose the difference between the volume of different database data [15], [16]. Moreover, dataset balance has been proved to help to improve the recognition accuracy in other fields [17], [18], but previous activity recognition algorithm based on deep learning ignore this.

In this paper, We evaluate the impact of training data volume and the balance between categories on the recognition accuracy. Different volume of data is used to training, forecasting and observing the impact of different volume of training data on the results. As far as we know, SMOTE algorithm can effectively solve the problem of some categories with less data volume have a lower recognition accuracy [19], [20]. But SMOTE algorithm is hard to apply to activity recognition data due to the data is time related, we propose a modified SMOTE algorithm for activity recognition and evaluate its impact on recognition accuracy.

The rest of this paper is organized as follow. In Section 2, We introduce the two deep learning algorithms(LSTM and CNN) which are used in this paper, as well as the SMOTE algorithm we modified it to make it suitable for human activity recognition. The Database introduction and data preprocessing, experimental analysis of influence factors and final results will be shown in Section 3. The paper is concluded by the summary of merits and limitations of the proposed method and the discussion of future work in Section 4.

## II. Deep Learning Evaluation Process

The purpose of this research is to study the impact of different data volume and data category balance on the human activities recognition. The proposed evaluation process, as shown in Fig 1, include data preprocessing, data quantity selection, training and classification, Dataset balance and accuracy comparison.

### A. Data Preprocessing

In this experiment, we used the acceleration data of the three axes(x,y,z). These raw data need to be pre-processed by steps such as uniform axis, de-gravity and timing window division. Since the acceleration data of a single point can not be identified, we use a sliding window to divide the human activity data. The sensor acceleration signal, which has gravitational and body motion components, was separated using a Butterworth low-pass filter into body acceleration and gravity.

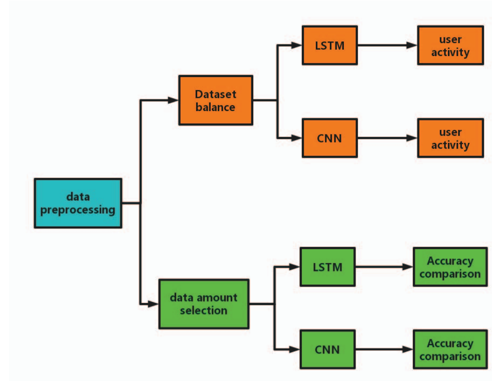


Fig. 1. Evaluation process

### B. CNN-based Activity Recognition

CNN is a multi-layer convolution neural network, each layer contains a number of two-dimensional plane and each plane includes a number of independent neurons. After the data enters the input layer, several training filters are used for carrying out the convolution operation and the initial feature matrix is obtained by the calculation of the excitation function. Subsequently, the feature matrix is down-sampled, and the feature map is obtained by an excitation function. Then repeat the above operations and connect the resulting feature graphs. The result is an extracted feature vectors. Finally, back propagation is carried out with the target of minimization error and the feature vector is trained by BP algorithm.

The loss function we used is Softmax function:

$$L_i = -log(\frac{e^{f_{y_i}}}{\sum_j e^j}) \tag{1}$$

The value in log function is the Softmax result of the correct classification in ith group data.

### C. LSTM-based Activity Recognition

Long short-term memory (LSTM) is a recurrent neural network (RNN) architecture published in 1997 by Sepp Hochreiter and Jrgen. Schmidhuber [21]. Unlike traditional RNN networks, the biggest feature of LSTM is the use of memory neurons whose data writing, saving and reading are controlled by special logic gates. These logic gates don't have diffuse properties, and their operational results and own actions don't affect the external neurons, but rather control the weight values of the connections between memory neurons and external neurons. Memory neuron is a linear neuron that contains input gate, output gate and forgotten gate, which can be used to select the correction parameter in the error function that decreases with the gradient. The structure of the LSTM node is shown in Figure 2. Each black node in Figure 2 is associated with an activation function and the middle Cell storage unit feeds back itself with 1 as a weight. While the internal self-connected dashed line is a constant error conveyor.

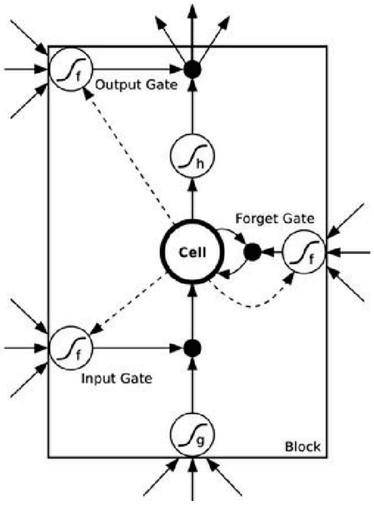


Fig. 2. LSTM node structure diagram

Human activity information is a classical time series or sequence analysis problem, it is suitable to deal with LSTM model. The loss function we used is as follows:

$$L_i = -log(\frac{e^{f_{y_i}}}{\sum_j e^j}) \tag{2}$$

The value in log function is the Softmax result of correct classification in ith group data.

### D. Synthetic Minority Over-sampling Technique(SMOTE)

Since the neural network tends to improve the accuracy of the overall data set and without considering the individual accuracy of each category. While using it to classify the activities, it will be inclined to improve the accuracy of categories with large data volume, while the smaller data volume categories will have higher misclassification rates. Due to the fact that the experimental data volume of dataset is not equal, there will be a higher misclassification rate of small data volume categories in the process of classification. The traditional method to solve the problem of less data volume category is the technique of resampling and oversampling, but it is only a simple copy of the data in small data volume category and easily lead to a overfitting phenomenon, while SMOTE avoid this phenomenon to a certain extent.

The principle of SMOTE is to randomly select a critical point from a small class, then randomly select a sample at the starting point and the critical point as the newly synthesized subset. Next, the new subset is added to the original data set. Then the extracted method is repeated in turn and each new subset is added back to the original data set. Compared with other oversampling techniques, the new subset which is randomly sampled by SMOTE has low correlation with the original data. It can balance the dataset and alleviate overfitting at the same time.

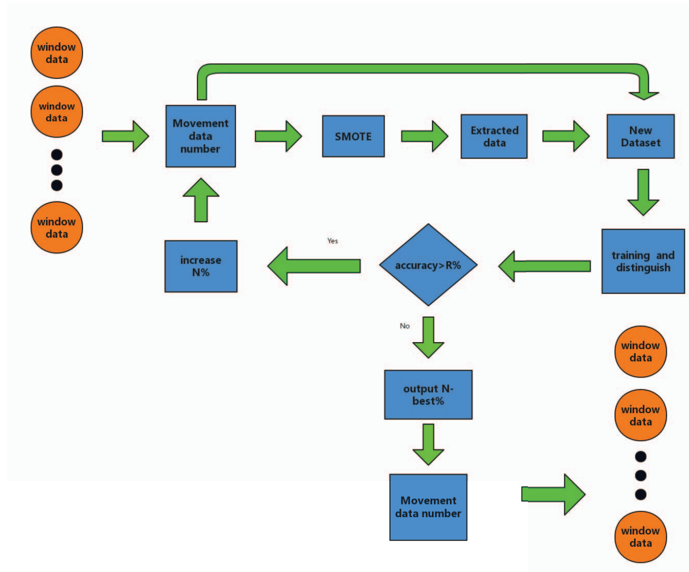


Fig. 3. The overview of SMOTE system

It should be noted that because we use sliding window to divide original data, the movement data which belongs to the same tester is divided into several windows. However, the traditional SMOTE algorithm aims at the expansion of continuous data and is not applicable to the segmentation data of human activity recognition. Therefore, we modified it to make it suitable for human activity recognition. The SMOTE system which we have modified it on the basis of the original algorithm is summarized in fig.4. Take an example to illustrate this algorithm. If increasing the movement data, such as downstairs, instead of only copying several windows data, we should copy the data of the entire downstairs movement which belongs to the same tester. So in our system, first of all, we number the data of less data volume category which belongs to the same tester. Making up a new dataset with the numbers and using SMOTE to expand it. After the new data is generated, it is added to the original data set and converted to window data. Then we train it by LSTM and CNN models and increase the percentage of new generated data gradually. Comparing all results to get the best increasing percentage. Finally, we convert the optimal data set into windows data. The following is the pseudo code of modified SMOTE algorithm.

## III. Experiments and Discussion

In this section we describe our data set and then present and discuss our results for the activity recognition task.

### A. Experiments Setup

In this experiment, we used three publicly available data sets, namely UCI HAR Dataset,Human Activities [22], Postural Transitions(HAPT) Dataset [**?**] and Human Activity Recognition in Ambient Assisted Living(HAR AAL) Dataset

Algorithm 1. Modified SMOTE algorithm

Initialize: Number of minority class samples $T$; Number of nearest neighbors k; Percentage of the resulting Dataset relative to original Dataset N%; Previous recognition accuracy R%;
Output: $\frac{N-best}{100} * T$ synthetic minority class samples
While $R - New\% \geqq R\%$
  For $100 < N < 200; N++$
    For $i = 1, 2, \cdots, T$
      Compute k nearest neighbors for i and save indices in the nnarray
      While $N \geqq 0$
        nn = random(1,k)
        For $attr = 1, 2, \cdots, numattrs$
          Compute:dif=Samples[nnarray[nn]][attr]-Sample[i][attr]
          Compute:gap=random(0,1)
          Synthetic[newindex][attr]=Sample[i][attr]+gap*dif
        Endfor
        Newindex++
        N=N-1
      Endwhile
    Endfor
    R-New%=train($\frac{N-100}{100} * T * Samples$+Dataset)
    If $R - New > R - Best$
      N-best=N
    Endif
  Endfor
Endwhile

[8]. Their data sampling frequency is 50Hz and all include six kinds of movements: walking, walking upstairs, walking downstairs, sitting, standing, laying. Because the sampling frequency is 50Hz, the sensor signals were pre-processed by sampled in fixed-width sliding windows of 2.56 sec and 50% overlap (128 readings/window). We unified the coordinate axes of the three databases, taken a sliding window with a length of 128 to separate it and carry out de-gravity processing by a low-pass Butterworth filter has a cutoff frequency of 0.3Hz. The orientation of the coordinate axis is shown in fig5.

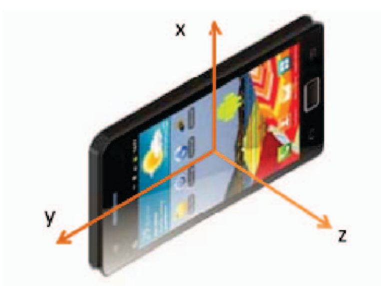


Fig. 4. Sketch map of coordinate axis

Since we have to consider the balance of activity class we counted the number of categories in the total datab before experiment.

According to table I, there are less data of the upstairs and downstairs movements. They accounted for only 14.6% and 13.5% of the volume of total data set. While the data volume of standing and laying movements accounted for 18.9% and 18.7% respectively of the total data.

In this study we built a 2x2 LSTM architecture with tensorflow: 2 residual cells as a block stacked 2 times for a total of 4 bidirectional cells, which is in reality 8 unidirectional LSTM cells. And we set up 32 hidden neurons in every layer.

TABLE I
DATA STATISTICS TABLE

| Activity | *UCI HAR* | *HAPT* | *HAR AAL* | *Data volume* |
|---|---|---|---|---|
| **Walking** | 661248 | 249600 | 106752 | 1017600 |
| **upstairs** | 592896 | 197112 | 87312 | 877320 |
| **downstairs** | 539904 | 189984 | 80400 | 810288 |
| **sitting** | 682368 | 249600 | 106752 | 1038720 |
| **standing** | 731904 | 274176 | 117120 | 1123200 |
| **lying** | 746496 | 272640 | 116352 | 1135488 |
| **total** | | | | 6002616 |

While in the CNN structure, we set up five hidden layers inside the neural network(including two convolution layers) and uses the max pooling function to process the feature vectors. The loss functions used by both models are softmax functions.

### B. Influence of the Dataset Volume on Accuracy

In order to observe the effect of the data volume on recognition accuracy, the total data set was divided into equal 6 parts. Then increasing the number of training data(1 million,2 million,3 million,4 million,5 million,6 million), and recording the accuracy of each experiment. The data was randomized and partitioned into ten equal parts, where 70% was used for training and 30% for testing.

According to table II, with the less data volume of training data, as the data volume increases, the recognition accuracy increases very quickly. However, when the number of data increases to 4 million, the growth trend of recognition accuracy also slows down. The results of the LSTM model are very close to CNN model. In most cases, the LSTM model's results are better than the CNN model's. The overall recognition accuracy of LSTM model is 93.9% and the CNN model is 93.3%.

TABLE II
RECOGNITION ACCURACY OF LSTM AND CNN MODEL

| | *% of Record Correctly Predicted* | |
|---|---|---|
| **Data volume** | ***CNN*** | ***LSTM*** |
| 1000436 | 64.8 | 63.9 |
| 2000872 | 74.5 | 74.1 |
| 3001308 | 82.6 | 82.8 |
| 4001744 | 87.9 | 88.4 |
| 5002180 | 91.7 | 92.2 |
| 6002136 | 93.3 | 93.9 |

Therefore, for the deep learning algorithm, the increasing of data quantity is helpful to improve the prediction results. The improvement in recognition accuracy is growing rapidly when the volume of data is small and then gradually slows down. So if you want to get a higher accuracy, a large volume of the data set is essential.

### C. Influence of the Dataset Balance on Accuracy

This section optimizes the optimal results of section B. Owing to the data volume of the six kinds of activities are quite different. The minimum data volume category are walking upstairs and walking downstairs, which account for only 14.6% and 13.5% respectively. While the maximum volume of category is laying, it accounts for 18.9% of total data set. The confusion matrix of the optimal results obtained in the previous section is shown below. The walking upstairs and downstairs movement have lower recognition accuracy. The higher misjudgment rate of sitting and standing movement is because their acceleration fluctuation trend is similar to a straight line and their magnitude is similar, too.

TABLE III
RECOGNITION ACCURACY OF LSTM AND CNN MODEL

| | *% of Record Correctly Predicted* | |
|---|---|---|
| | ***CNN*** | ***LSTM*** |
| **walking** | 98.2 | 98.3 |
| **upstairs** | 87.5 | 88.4 |
| **downstairs** | 96.7 | 96.8 |
| **sitting** | 89.3 | 90.4 |
| **standing** | 88.4 | 88.6 |
| **laying** | 100 | 100 |
| **Overall** | 93.3 | 93.9 |

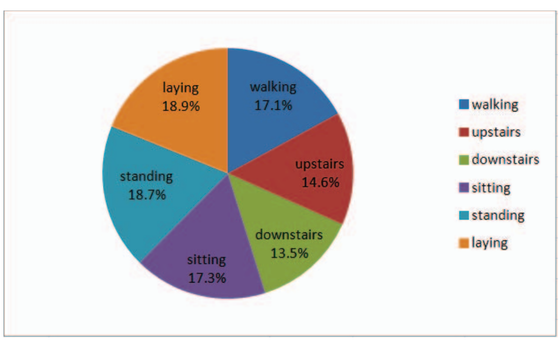


Fig. 5. Raw Dataset

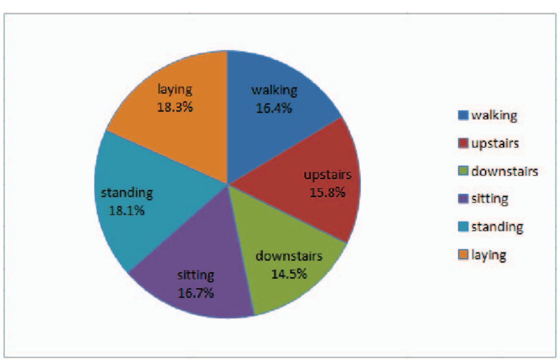


Fig. 6. SMOTE generated Dataset

The SMOTE algorithm is used for increasing the data volume for upstairs and downstairs movement. It should be noted that because we use sliding window to divide original data, the same type of movement's data which belongs to the same tester is divided into several windows. Therefore, before data processing, the data of each window are attributed to the original movement, and then the data balance operation is carried out according to the number of the movement. On the premise of avoiding overfitting phenomenon, the data volume for upstairs was increased by 104568 and it increased by 87888 for the downstairs movement. We can observe the changes of data volume for each category by comparing the following two fan diagrams.

CNN and LSTM model are used to train the newly generated data set and observe whether the forecast results have improved or not. The prediction is shown in table IV.

TABLE IV
RECOGNITION ACCURACY OF OPTIMIZED LSTM AND CNN MODEL

| | *% of Record Correctly Predicted* | |
|---|---|---|
| | ***CNN*** | ***LSTM*** |
| **walking** | 98.2 | 98.3 |
| **upstairs** | 96.4 | 96.2 |
| **downstairs** | 98.2 | 99.4 |
| **sitting** | 89.9 | 90.4 |
| **standing** | 88.7 | 88.6 |
| **laying** | 100 | 100 |
| **Overall** | 95.1 | 95.4 |

In LSTM model, the recognition accuracy of walking upstairs movement is increased from 88.4% to 96.2%, and it is also increased from 96.8% to 99.4% for walking downstairs movement. The same to LSTM, in CNN model, the recognition accuracy of walking upstairs movement is increased from 87.5% to 96.4%, and it is increased from 96.7% to 98.2% for walking downstairs movement. That indicates that the operation of balanced data set is helpful for improving the recognition accuracy of category with less data volume. Moreover, because of the increase in the recognition accuracy of minority classes, the likelihood that will misjudge to other movements is correspondingly reduced. So from the overall point of view, the overall recognition accuracy of the LSTM model is 1.5% higher than before, and the accuracy of the CNN model is improved by 1.8%. Therefore, the operation of balanced data set can also improve the overall recognition accuracy of entire data set. More detailed results are presented in Tables V-VI, which show the confusion matrices associated with each of the two deep learning algorithms.

## IV. CONCLUSION

This work presents the effect of two deep learning algorithms(LSTM and CNN) on the human activity recognition and analysis two influence factors of recognition accuracy based on deep learning: data volume and data set balance.

TABLE V
RECOGNITION ACCURACY OF OPTIMIZED CNN MODEL

| | ***Predicted Class*** | | | | | |
|---|---|---|---|---|---|---|
| | **walk** | **upstairs** | **downstairs** | **sit** | **stand** | **lay** |
| **walking** | 781 | 10 | 1 | 0 | 2 | 0 |
| **upstairs** | 14 | 736 | 15 | 0 | 0 | 0 |
| **downstairs** | 0 | 4 | 698 | 0 | 0 | 0 |
| **sitting** | 1 | 5 | 3 | 730 | 69 | 0 |
| **standing** | 2 | 7 | 5 | 86 | 776 | 0 |
| **laying** | 0 | 0 | 0 | 0 | 0 | 885 |

TABLE VI
RECOGNITION ACCURACY OF OPTIMIZED LSTM MODEL

| | ***Predicted Class*** | | | | | |
|---|---|---|---|---|---|---|
| | **walk** | **upstairs** | **downstairs** | **sit** | **stand** | **lay** |
| **walking** | 781 | 10 | 1 | 0 | 2 | 0 |
| **upstairs** | 14 | 736 | 15 | 0 | 0 | 0 |
| **downstairs** | 0 | 4 | 698 | 0 | 0 | 0 |
| **sitting** | 1 | 5 | 3 | 730 | 69 | 0 |
| **standing** | 2 | 7 | 5 | 86 | 776 | 0 |
| **laying** | 0 | 0 | 0 | 0 | 0 | 885 |

In order to observe the effect of the data volume on forecast results, we increase the number of training data, and find that when the data volume is small($< 4M$), the recognition accuracy increased quickly with the increase of the quantity of training data. However, the growth trend of recognition accuracy slows down when the data quantity reaches 4 million. It is known that the 93.9% accuracy for LSTM model and 93.3% accuracy for CNN model in the case are entried in the total database.

Modified SMOTE algorithm is proposed in our analysis for balancing data set. In the premise of avoiding fitting phenomenon, it increases the data volume of two movements(upstairs and downstairs), so that the recognition accuracy of LSTM and CNN models is increased by 1.8% and 1.5% respectively. In LSTM model, the recognition accuracy of two movement categories of less data volume is increased by 7.8% and 2.6% respectively, and they also increase by 8.9% and 1.5% in CNN model. This illustrates that the data set balance operation can not only improve the recognition accuracy of the categories with less data volume, but also help to increase the overall accuracy.

It is found that the distinction between standing and sitting movement is not very obvious. This phenomenon isn't related to the data volume and the balance between categories. It may be due to the features required for dynamic and stationary state identification are different, and these two categories of movement need to be dealt with separately. This problem deserved further study in future.

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