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Predicting Lifespan of Aircraft Engines Using LSTM

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ABSTRACT: Just like human beings, machines also have a lifespan. However, unlike that of human beings, the lifespan of aircraft engines can be renewed for extended periods of time. Though, at a given point of time, aircraft engines can be found in a working condition, it is often difficult as to when it would fail to function resulting in aircraft crashes and the dangers thereof. Hence, it is crucial to predict in advance as to how sooner or later the aircraft would stop functioning so that the remedial measures can be taken care of. Aero engine is a kind of refined and extravagant industrial product. Catastrophic failures can be avoided and economic losses can be reduced by estimating the lifespan of aero engines. The goal of this work is to use a neural network with Long Short-Term Memory (LSTM) to get good performance in detecting and predicting complex operations, hybrid error faults, and impregnable noises. The work accurately predicts when an aeroplane engine will break down and finds the problem before it happens. LSTM neural networks are used in the proposed techniques to make the application work better. LSTM methods use time stamps (steps) to look at past data and put together the needed dataset.

KEYWORDS: Long Short-Term Memory Aircraft, Hybrid Error Faults, Impregnable Noises.

I. INTRODUCTION

During the earliest periods of time when computers were not so advanced, there were times when aircrafts were made with very limited number of sensors as the other sensors values didn't play a significant role on the condition of the engine. Since the advancement of computers have taken to such an extent that we can use other sensor values beneficially. Having embedded all the 21 sensor values inside an engine helps us to do predictive maintenance. This can lessen the exacerbation of existing problems, efficiently saves time and makes it robust. The sensors embedded in the engine provide abundant earlier data that helps in understanding the present state of an aircraft engine. This data can be stockpiled into either physical local drives or into Cloud based Servers, which constantly keeps on collecting the real time data and store it so that it can be used at any point of time in need. This behaviour of sensor data provides a convenient way to predict when the aircrafts equipment's can possibly fail. Hence, reducing the need to physically go work on engines which can now be done by sitting at any desired place, with just the access of engine sensor data.

Predictive maintenance has received lots of attention recently. Therefore, the Recurrent Neural Network (RNN) and Long Short Term Memory (LSTM) techniques are a part of deep learning methods. These are utilized to time stamp the data sets that makes it so efficient that it goes back 60time stamps with past data to predict the actual or current lifespan. The motive of using LSTM approach is to arrive with higher accuracy rates as this technique is capable of learning and training itself by using its own data. This makes it one of the best techniques to predict the future values efficiently having an accuracy of 96%.

The first step towards this approach is to calculate the remaining useful life of the engine using the number of cycles the engine has completed during its course of travel. Clearly LSTM is an appropriate technique for understanding the real time data and processing it to efficiently predict the future values in a time series prediction. The time index or stamps are considered to be flight cycles which give enough computational time for calculation. The data used in this is taken from NASA's prognostic data repository, which particularly contains three kinds of aircrafts i.e. ID1, ID2 and ID3 along with its data.



The health monitoring dataset of aircraft turbofan engines taken from NASA is used to calculate the trajectory of health parameters that help in finding the remaining useful life of defected component. Using this data repository, a model using LSTM is proposed. This model can estimate the remaining useful life and predict when it will fail in future, therefore providing better service to the aero industry. The aim of this work is to accurately predict the remaining useful life using raw data, sensors that can effectively reflect any degradation in engine.

II. RELATED WORK

[1] The Vehicle's Velocity Prediction Methods Based on RNN and LSTM Neural Network Authors: Yi Du, Naxin Cui, Huixin Li, Hao Nie, Yuemei Shi, Ming Wang and Tao Li IEEE Xplore (2020)

All over the world, electric cars are becoming more and more popular. How energy is distributed and managed will depend on how fast HEVs and PHEVs are expected to go in the future. In this study, models have been made that use Recurrent Neural Networks (RNN) and Long Short Term Memory (LSTM) Neural Networks to predict how fast a car will go in the future. Validating the test data can help both models predict how fast a car will go better. But the root mean square error (RMSE) of the LSTM prediction model is less than that of the RNN model as the length of the prediction gets longer. This means that the LSTM prediction model is better at figuring out how fast a car is going. Based on deep learning, the study suggests a way to figure out how fast a car is going. Deep learning builds on what neural networks have always done well and can look deeper into how driving information from the past and driving information from the future might be linked. This makes it easier to figure out how fast a car will go in the short term. The RNN and LSTM models are used to predict how fast a car will go, and the Artemis Motorway is used to test how well these two models work. The test results show that LSTM is better at predicting short-term velocity when the training set is made up of historical velocity. This method is more accurate than RNN because the difference between the predicted speed and the actual speed is small on average. So, LSTM works well with time series that are made up of data on how fast vehicles move. This paper talks about a way for EMS to make predictions.

[2] Aero Engine Fault Prediction Based on Bidirectional LSTM Neural Network Author: Yue Zhang 2020 International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE), IEEE Xplore (2020)

As the power system of an aeroplane, an aero-safety engine's and reliability affect how well the whole plane works and, more importantly, people's lives and property. Based on the idea of bi-directional LSTM neural modelling and information fusion, this paper creates a multi-fault characteristic parameter prediction model by combining the relationship between the sampled data of several characteristic parameters of an aircraft engine and the actual characteristics of the prediction sequence. The wavelet packet decomposition technology is used to get the energy values of each frequency band of the rotor vibration signal as input values for the bidirectional LSTM neural network system, to predict the energy changes of each frequency band, to reconstruct the feature vector made up of the predicted values, and to apply to the fault prediction analysis of the aero-engine rotor. In this study, a bi-directional LSTM neural network is used to group together real-time data from aero-engines and data from the maintenance database. In fault prediction, the highly nonlinear mapping between input and output can be made by adding the action functions together many times. Research shows that the method can accurately estimate the health performance parameters and, to a certain extent, predict when the engine will break down, as long as the health parameters are measured through experiments. The prediction error is smaller and the accuracy of the prediction is higher, which is very important for how well the aero-engine rotor works and how long it lasts. In the same way, this model can also be used to predict faults in other rotations. It has been shown that the proposed bi-directional LSTM model is good for predicting aero engine faults. The model has high prediction accuracy and a good chance of being used.

[3] Applications of LSTM Model for Aero engine Forecasting Authors: Peng Li, Wei Niu 2020 7th International Conference on Dependable Systems and their Applications (DSA), IEEE 2020

Prediction is the most difficult and challenging comprehensive technology because it is such an important part of PHM. Its goal is to predict when a component or system will fail and how long it will still work. It also helps with operation planning and maintenance decisions. Because the current predictions of aircraft engines aren't very accurate, a particle swarm optimization LSTM neural network-based method for predicting the RFL of an aircraft engine is proposed. The research object for this method is a huge amount of historical information about a certain type of aeroplane engine. On the Hadoop+Spark platform, the HDFS is used to store a lot of data, and the Spark engine is used to do parallel

computing in memory. Fse training data is used to build an LSTM neural network that can predict an aircraft engine's RFL. The result shows that the proposed method is better at making predictions than the traditional LSTM algorithm model and other computing frameworks. Spark works faster with data. To test how well the proposed method works, the speedup is increased by an order of magnitude. A prediction model is made based on the Hadoop+Spark architecture. We use the Hadoop Distributed File System (HDFS) in the Hadoop platform to store the aircraft engine data collected by the airborne sensors. We also use normalisation and principal component analysis (PCA) to prepare the data. Parallelization of data is done in the Spark framework, and the algorithm model is optimised and checked in an iterative way. Hadoop+Spark ecosystem and its parts are built on the big data platform of the PHM system. They use big data technology to combine multiple characteristic parameters for data mining and analysis, and they propose a method for predicting the RUL of aircraft engines based on the PSO-LSTM. The method makes it possible to predict the RUL of the aeroengine and gives technical support for changing aircraft from regular and state maintenance to predictive maintenance.

[4] Aero-Engine Remaining Useful Life Estimation based on 1-Dimensional FCN-LSTM Neural Networks Authors: Wei Zhang, Feng Jin, Guigang Zhang, Baicheng Zhao, Yuqing Hou IEEE Xplore (2019)

A 1-Dimensional Fully-Convolutional LSTM algorithm is proposed as a fast and accurate way to figure out how long aeroplane engines still work. First, SVM is used to find failures by looking for things that aren't normal. It will also help label training data. Then, K-means clustering is used, which has new ways of working that can be used in different ways of working. Last, the main algorithm for estimating is a combination of Convolutional neural network and LSTM. The idea is judged using NASA's C-MAPSS dataset, which can be used by anyone to check on the health of aircraft turbofan engines. To see how accurate the proposed algorithm is at making predictions, it is compared to a single LSTM and a 1-D CNN, and it is shown to be more accurate. As a type of RNN, LSTM is designed to avoid long-term dependence and gradient vanishing. It is also made up of LSTM memory blocks that repeat, but each block has three gates—an input gate, a forget gate, and an output gate—that decide what information will be added to the memory cell and what information will be thrown away. In this paper, a deep learning algorithm called 1 Dimensional Fully-Convolutional-LSTM neural networks is proposed as a way to solve the bottleneck problem of high-precision RUL for aero-engines. We use the SVM classifier as a failure detector to find failures and make sure that the RUL labels are right. Also, the traditional clustering method k-means is used to pull out more operation condition features to help find the real physical degradation mechanism behind sensor readings in modes of operation that are complex and changeable. All of these will be better at making predictions than a single LSTM and a 1-D model because they have a simple structure, few parameters, and less error. CNN. The proposed neural network algorithm can help PHM of complex engineering systems so that maintenance costs are lower and catastrophic failures happen less often.

[5] The Improvement of Remaining Useful Life Prediction for Aero-engines by Injecting Noise Authors: Junxuan Tang, Nailong Wu, Lei Xiao, Jingsong Zhao 2020 Global Reliability and Prognostics and Health Management (PHMShanghai), IEEE Access (2020)

In the last few decades, there has been a lot of research on how to figure out how long a machine will still be useful (RUL). Most RUL prediction methods try to get rid of noise in the observation data because noise is seen as an annoying disturbance. On the other hand, noise can be useful if it is used in the right way. The paper suggests a new way to predict RUL by adding noise to an LSTM neural network on purpose. This helps the network get a better idea of RUL. The added noise meets the noisy expectation maximisation (EM) positivity condition and makes the RUL prediction results better. So, the method that is being suggested is called a noise-boosted RUL prediction method. The paper is an early attempt to predict RUL for aeroengines by adding noise on purpose. Comparing the new method to the well-known C-MAPSS dataset for aeroplane engines shows that it works. The predictions have shown that adding noise on purpose makes them more accurate. The paper looks at a new RUL prediction method for aero engines that uses noise that was added on purpose to make the prediction more accurate and reliable. When noise is put into a neural network's output layer, it "pollutes" the target output while the network is being trained. The presentative degradation features change over time and in a certain order, so an LSTM network is used to predict RULs. Even though noise injection is used to mess up the LSTM network's target output, this RUL prediction method is better because of it. Most of the other ways to train a neural network involve filtering out or getting rid of noise. The new RUL prediction method with added noise is better than some of the best methods available right now.



III. METHODOLOGY

DATASET

A NASA repository data set [6] on aircraft engines is used to train and test the model. It has data of 21 sensor measurements operating under 3 different operating modes of an engine. The schema of dataset is as shown in below Table 5.1. The dataset consists of time series data of various engines manufactured under different conditions by different manufacturers which describes the dynamic nature of dataset. Hence every engine has different degree of initial condition. Every engine operates at normal conditions in the beginning and starts developing faults after number of cycles and fails gradually. Input is fed in the form of 3 datasets

- Training data to train the model
- Test data to predict the remaining life span of engines
- Truth data which contains the actual lifespan of engines, to calculate accuracy of the model

<i>Index</i>	<i>Data Fields</i>	<i>Type</i>	<i>Description</i>
1	Id	Integer	Aircraft Engine Identifier
2	Cycle	Integer	Time in cycles
3	Setting1	Double	Operational Setting 1
4	Setting2	Double	Operational Setting 2
5	Setting3	Double	Operational Setting 3
6	S1	Double	Sensor Measurement 1
7	S2	Double	Sensor Measurement 2
8
9	S21	Double	Sensor Measurement 3

Table 5.1: Features included in dataset

At the beginning of the series, the engine is working as it should. After a lot of cycles, something goes wrong with the engine, and it starts to break down. As part of our plan, we gave them three sets of text files with data to use for training, testing, and figuring out how accurate they were. The data sets that were there were

- Training data: It shows how long the engine ran before it broke down.
- Testing data: It is a record of how the aircraft engine ran without any failures..
- Ground truth data: It shows how many real cycles are left for each engine in the testing data.
- In the training set, there are more and more mistakes until the system breaks. In the test set, the number of times ends before the system fails.

PRE-PROCESSING

Initially, all the null values are deleted. Input data is normalized with the help of scikit learn library. The major drawback of this normalization is that sensor measurements can be constant in few cases which will result the variance to be Zero. Hence dividing the normalized input by variance is ignored in such cases. The output is in the form of 1-1000 cycles. It is normalized using min max scaller and scaled down into 0-1 to ensure better understanding by neural networks. The output is classified in terms of minimum lifespan, average lifespan and maximum lifespan.



- Input normalization: We normalised the data that came in by using the mean and the range. It's important to keep in mind that in some cases, the number of operating conditions means that sensor readings are likely to stay the same, which can make the related differences equal to zero. In these situations, you don't need to divide by variance.
- Output normalization: RUL estimate values are usually in the range of 1 to 1000, while probability values describe the results of fault diagnosis in the range of 0 to 1. To make sure the cost function is balanced, we try to normalise it by dividing the RULs into three groups: maximum life span, average life span, and minimum life span.

TRAINING AND TESTING THE MODEL

The dataset is divided into 80% of training data and 20% of test data using Numpy library. The Machine learning algorithms enables the machine to learn from itself with the help of training dataset without any explicit instructions. These machines identify the patterns from training data and predict the lifespan of engines from test data. Scikit learn libraries are used to scale down the results of test data and compared with the ground truth data to calculate the accuracy of the model.

PREDICTION USING MACHINE LEARNING

Machine Learning (ML) lets computers use the data they have to learn on their own, without being programmed. These machines can respond to new information based on what they already know. Prediction is one of the most important things that Machine Learning is used for. There are two types of ML. They are put into "Supervised" and "Unsupervised" groups. In supervised learning, the output classes are used to train the machine. These classes are part of the dataset. On the other hand, in unsupervised learning, the output classes are unknown, so the data is split into unknown classes. In this paper, supervised machine learning, which is used to make predictions, is the method that is used. The turbo fan engine dataset has two sets: the training set and the test set. Both the training data and the test data have the real RUL value, which we want to predict.

IV. EXPERIMENTAL RESULTS

Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are found. MAE is the average difference between how long someone actually lives and how long they are expected to live.

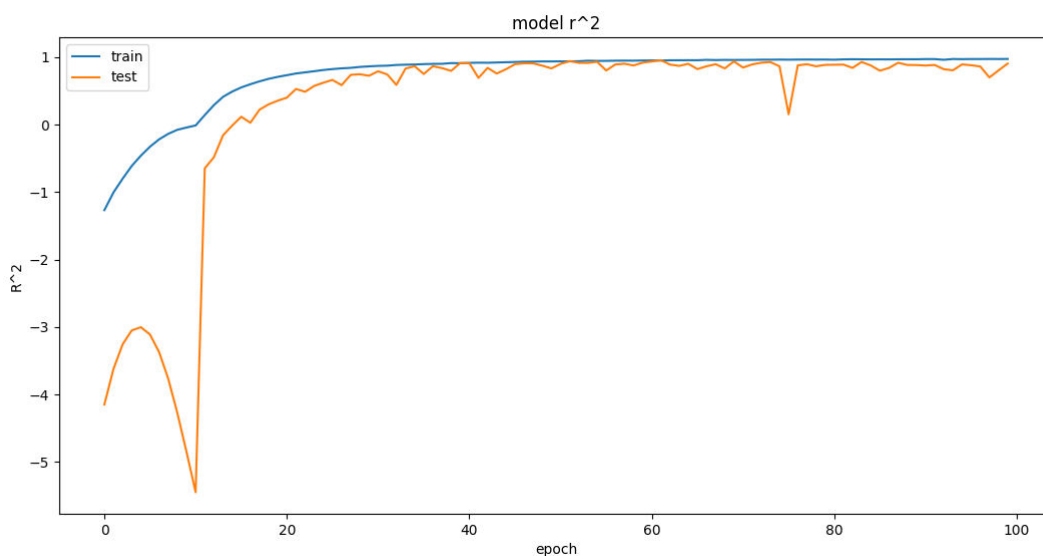


Figure 6.1 The graph of r^2



The graph above shows how closely the test data moves towards training set with the increase in number of epochs.

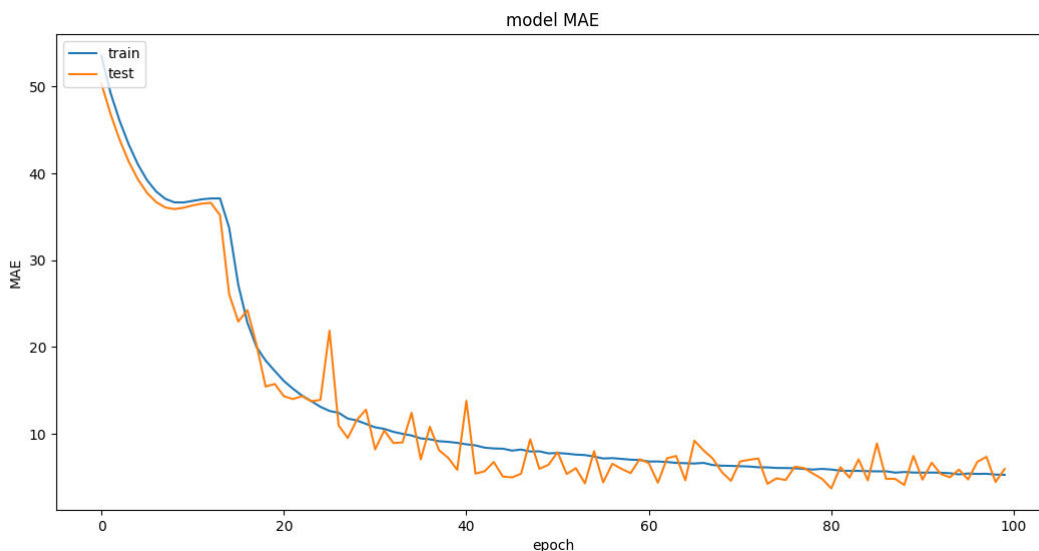


Figure 6.2 The graph of MAE

This graph represents the mean absolute error being reduced with the increasing number of epochs. As we can see in the above graph, initially the value of MAE is at peak, which gradually reduces as the number of epochs increases.

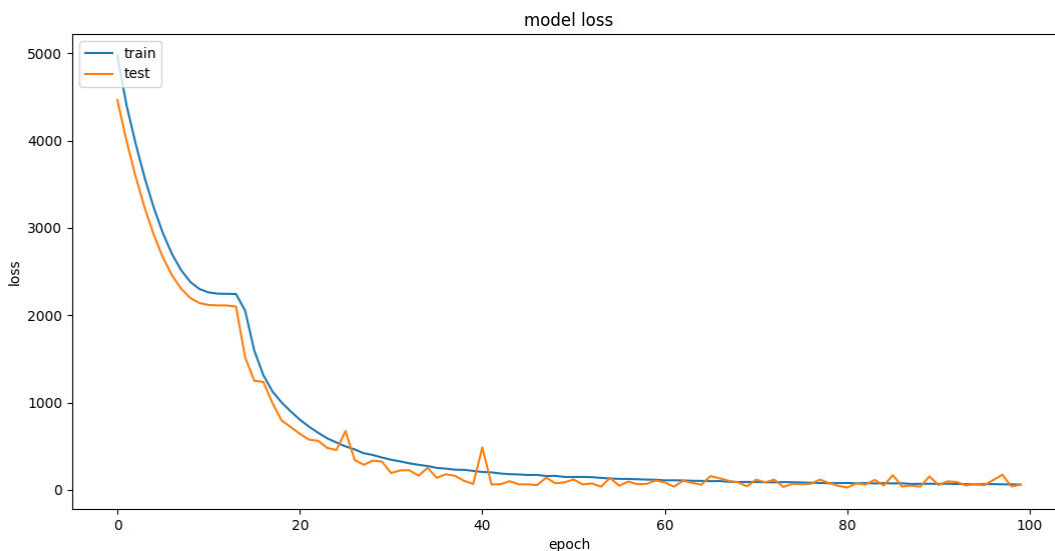


Figure 6.3 The graph depicting loss

The graph represents the decreasing loss with increasing number of epochs. Initially, the value of loss is at peak, which gradually decreases as the number of epochs increases. The graph shows that the trained data and test data are close, except for some uncertainty of the test data.

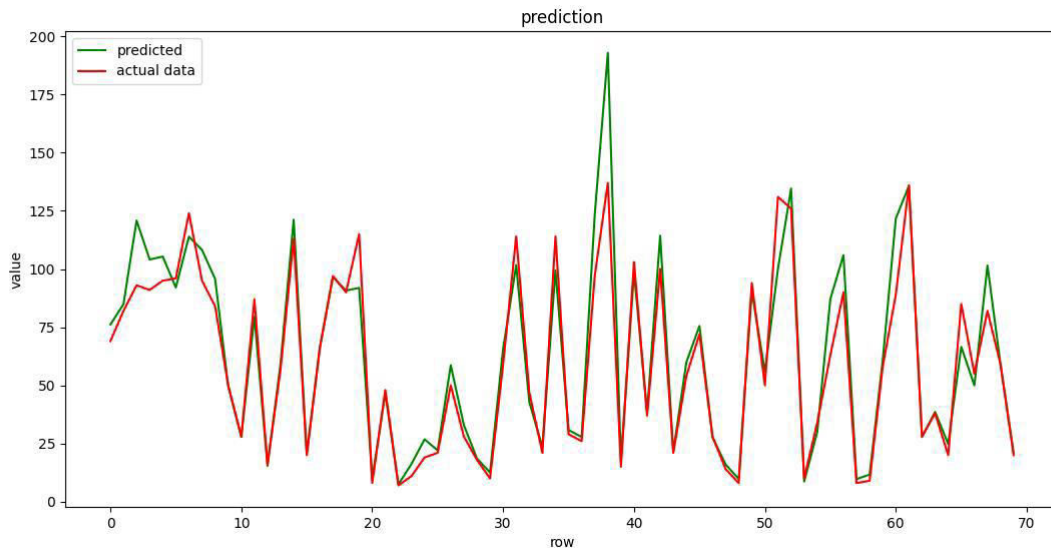


Figure 6.4 Plot of predicted and actual data

A graph is plotted with the help of matplotlib python library between predicted life spans of test data to actual lifespan provided in truth data. The difference in the actual curves and predicted curves accounts for RMSE value which shows us the accuracy of the model. By implying LSTM technique we have got 96% accuracy proving this model to be most reliable to predict remaining lifespan of aircraft engines. Figure 6.5 shows the Accuracy of the model, RMSE loss and MAE loss at the end of 100 epochs.

MAE :
7.50902795791626

R^2 :
0.8732883334159851

ACCURACY :
0.9609926857412653

Figure 6.5 MAE loss, R² loss and accuracy of the proposed method

It consists of various graphs, depicting the mean squared error loss, root mean squared loss and the accuracy obtained by the proposed method

V. CONCLUSION

The LSTM neural network used in this model works well to solve a number of very difficult problems and is also a good way to take care of the maintenance of an aeroplane engine. The proposed LSTM neural network-based method works very well, as shown by the very low MAE and R2 values. This means that the model's estimate of the remaining useful life is very close to the real value. This proposed LSTM system has a high level of performance, and this method makes it possible to use a lot of historical data so that it can make very accurate predictions. So, it's safe to say that this deep learning method is much better than the old ways of doing things. The MAE and R2 values for the proposed LSTM-RNN-based approach are lower, which means that the RUL predicted by the LSTM-RNN model for this set of



data sets is very close to the actual value. The results of the experiments clearly show that the proposed method can predict the RUL of aircraft engines accurately. Also, we can say that the LSTM-RNN prediction method is better than the traditional statistical probability regression method when there are a lot of data. The only problem with this method is that if there isn't much data in the past, it can lead to a lot of uncertainty, which makes it hard to predict the value. So, for this method to accurately predict the value, it is very important to have a large number of up-to-date data sets.

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