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Cloud Computing Based Smart Garbage Monitoring System

Jetendra Joshi, Joshitha Reddy, Praneeth Reddy, Akshay Agarwal, Rahul Agarwal, Amrit Bagga, and Abhinandan Bhargava
Department of Computer Science,
NIIT University, Rajasthan, India

Abstract— **Healthy environment is imperative to a healthy and happy community. With the age old system of hiring people to regularly check and empty filled dustbins, the process has been prone to human error and neglect. Additionally, due to different frequency of usage of dustbins in different areas, routine checks which are based on time crevices is inefficient because a dustbin might get filled early and may need immediate attention or there might not be any need of a routine check for a long period of time. This makes present system resource expensive and ineffectual, as overflowing, stinking dustbins become more of a problem than a solution. In this paper we present a solution about the SmartBin is a network of dustbins which integrates the idea of IoT with Wireless Sensor Networks. We also put forward the concept of a network of smart garbage bins based on the Stack Based Front End approach of integrating Wireless Sensor Network with the Cloud computing and discuss how Machine Learning techniques like Decision Forest Regression can be applied to the sensor data leveraged by the system to gain useful insights to improve the efficiency of the garbage monitoring .**

Keywords— Smart Devices; Internet of Things ; Wireless Sensor Network ; Stack Based ; Front End ; Machine Learning; Decision Forest Regression; Garbage Monitoring System.

I. INTRODUCTION

A healthy environment is necessary if we want to stay healthy. However, in today's fast paced life individuals scarcely have time to stop and configure things manually and hence the idea of automation is by and large broadly embraced. Either because of our fast paced life or because of our casual approach often small though critical things like cleanliness gets ignored. In big institutions or a city under a municipal corporation where there are an extensive quantities of garbage bins deployed and workers are kept specifically for this task, the antiquated technique for physically hunting down filled garbage bins is wasteful and does not run well with the technological era we are in. Routine checks for cleaning the garbage bins which depend on time crevices are wasteful in light of the fact that a dustbin may get filled early or may get tampered and might require prompt consideration or there might not be any need of a routine check for a drawn out stretch of time. Likewise, to save fuel and time and make the entire process more effective and convenient, the workers going on routine check should know the shortest route comprising of all the filled garbage bins.

Several challenges exist in the design of such systems for a successful Smart City Implementation such as prolonging the battery life of sensor nodes, setting up the infrastructure for low powered M2M communication over longer distances (between a gateway and a distant central server), redesigning the WSN architecture pertaining to a particular Smart City Application etc. However, in this paper we will discuss about how a sensor network of garbage bins could be connected to the Internet analyzing the various integration approaches and also how Machine Learning techniques can be exploited to make the entire system more efficient. The paper has been organized in 7 sections. We have passed through the Introduction. In Section 2, we have described the related work. The Section 3 describes the background of the project . Section 4 describes the problem statement in the Smart Bin based management system. Section 5 explains the Smartbin system architecture. In Section 6 we explained how the whole system is integrated with the cloud ad the performance enhancement to give brief description about technology . In the Section 7 we conclude the paper .

II. RELATED WORK

Narayan et. al [1] have proposed a Smart Bin implementation for Smart Cities in which they have associated the huge garbage bins present in every locality with a hardware device. The hardware device is essentially a PIC-16F73 microcontroller connected to an Ultrasonic sensor (HC-SR04) to gather information about the filled trash level and a GSM module to send instant messages about the filled level to a central garbage analyzer and a few other components. Further analysis and predictive modeling is applied on the data received at the garbage analyzer end which is further linked up to an application that the end users can use. Utilizing GSM is costly and has a higher battery inefficiency associated with it and is not a good technology to use considering a city wide deployment and that we need the garbage bins to sustain a long period of time with no need of replacement of batteries.

Moreover, cellular technologies are not geared for battery efficiency or moving little bits of data inexpensively. [2], [6] have also proposed a sensor GSM integrated model for Smart Garbage Bin implementation. Tony et. al [3] have proposed a novel battery level aware clustering family of schemes called BLAC which they have implemented for a network of smart bins. BLAC is a distributed clustering algorithm providing non-overlapping multi-hop clusters with energy concerns that extends the lifetime time of the first dying node to about 300%. For peer to peer communication among the bins Tony et .al [3] have used ZigBee and for long range communication with the base station they have used GPRS. GPRS consumes more power and despite only the cluster heads communicating with the distant base station over the GPRS link the nodes would eventually die off. These networks are considerably less adapted to situations where, either the unit transmits very little, either it operates in battery mode (no regular power supply), or either if its overall size would be truly minimized. Vikrant et. al [5] have proposed a smart garbage management system similar to [1] just that they have used Atmel328 microcontroller and IR sensors for detecting the garbage filled level. [4] have discussed about scalable sensor networks. [8] have discussed on waste management and [7] have discussed about a RFID based waste management system. C.Alcaraz et. al [11] have discussed about the various approaches of integrating Wireless Sensor Network with the Internet of Things. [12] and [1] have discussed about how data analytics can be applied on such systems.

III. Background

WSN and IoT Integration Approaches

The approaches for integrating Wireless Sensor Network into the Internet of Things are classified into two categories: Stack based and Topology based [11]. The stack based classification includes the Front End, Gateway and TCP approach. In the stack based classification the integration is based on the similarities in the network stack of WSN and the Internet. In the Front End solution, the external Internet hosts never communicate directly with the sensor nodes rather the communication takes place via means of interfaces such as Web Services. [10] In the Gateway approach the Internet hosts can communicate with sensor nodes indirectly via the base station that acts as an application layer gateway translating the lower layer protocols from both networks and routing the information from one point to another whereas in the TCP/IP approach each sensor node implements the TCP/IP protocol stack and the communication between a sensor node and the Internet can take place directly. The TCP/IP protocol stack is made compatible with the underlying IEEE 802.15.4 using an adaption layer approach known as the 6LoWPAN.

The Topology based classification includes the Hybrid and the Access Point approach. [11] In the Topology based classification the integration is based on the actual location of the nodes that provides the access to the Internet. In the hybrid approach a few sensor nodes located at the root of the network provide access to the Internet which maintains the TCP/IP protocol stack whereas in the Access Point Approach a backbone of devices allows the sensing nodes access to the Internet in one hop. In our system we have made use of the Stack based front end solution in case of this system the bins need not be aware of the Internet and external Internet hosts querying each bin individually as in case of TCP/IP is not required. Also making the sensor nodes Internet enabled will make the system vulnerable to many different types of attacks ranging from DoS attacks to exploit attacks.

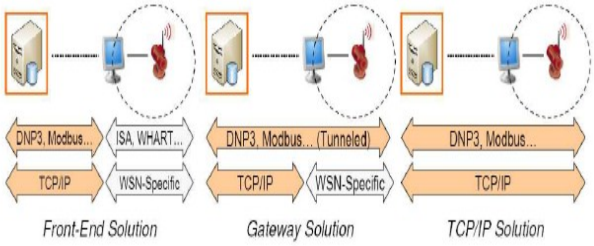

Fig. 1. Stack Based Approaches

6LoWPAN

The 6LoWPAN technology utilizes IEEE 802.15.4 to provide the lower layers for this low power wireless network system. While this seems a straightforward approach to the development of a packet data wireless network or wireless sensor network, there are incompatibilities between IPv6 format and the formats allowed by IEEE 802.15.40. [11] This differences are overcome within 6LoWPAN and this allows the system to be used as a layer over the basic 802.15.4. In order to send packet data, IPv6 over 6LowPAN, it is necessary to have a method of converting the packet data into a format that can be handled by the IEEE 802.15.4 lower layer system. IPv6 requires the maximum transmission unit (MTU) to be at least 1280 bytes in length. This is considerably longer than the IEEE802.15.4's standard packet size of 127 octets which was set to keep transmissions short and thereby reduce power consumption. To overcome the address resolution issue, IPv6 nodes are given 128 bit addresses in a hierarchical manner. The IEEE 802.15.4 devices may use either of IEEE 64 bit extended addresses or 16 bit addresses that are unique within a PAN after devices have associated. There is also a PAN-ID for a group of physically co-located IEEE802.15.4 devices.

Application	APPLICATION	
Transport	UDP	ICMP
Network	IPV6 with LoWPAN	
Data Link	IEEE 802.15.4 MAC	
Physical	IEEE 802.15.4 PHY	

Fig. 2. 6LoWPAN protocol stack.

IV. Problem Formulation

The different frequency of usage of dustbins in different areas, routine checks which are based on time crevices is inefficient because a dustbin might get filled early and may need immediate attention or there might not be any need of a routine check for a long period of time. Is there any smart method by which we can integrate hardware and software resources . How can we use the cloud computing technique effectively with the sensor network . Is there optimized way to use the shortest path for the garbage collection machine so that throughput of system can be increased. What machine learning techniques can be used in cloud computing scenario to enhance the performance .

V. SmartBin System Architecture

In this section we describe the major components of the system as shown in Fig 3. As already mentioned we are using a garbage monitoring system as a test bed which have been tested at NIIT University, Neemrana but it only stands as a proof of concept and the architecture can be applied to any other services as well. We also discuss the working methodology of the entire system and finally discuss about the mobile application which is one of the main aspect of the research because mobile phones are commonly used and it is the most convenient way in which information can be delivered to the user.

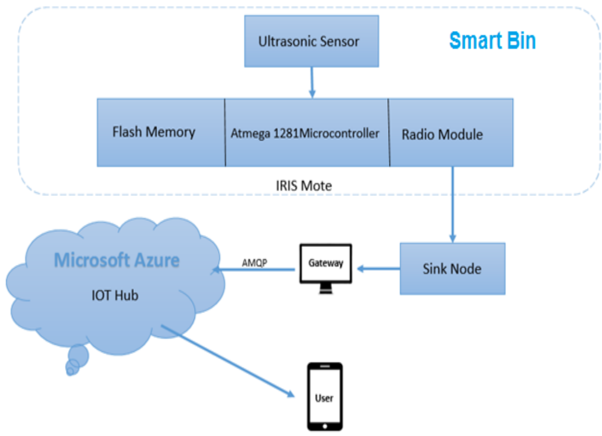

Fig. 3. System Architecture

Technologies Used

A Hardware

WSN Motes. There are a number of commercially available platforms, like TelosB, MICA Z, IRIS, Tiny Node, etc. In this paper we have utilized Iris bits alongside MDA100 sensor boards for distance monitoring application.

IRIS. The IRIS bit are utilized for empowering low power remote sensor systems. The utilization of IRIS advantages the clients with a wide assortment of custom detecting applications giving around three times enhanced extent for radio correspondence and twofold the measure of the project memory over past eras of MICA Z Motes. Its weight is around 10 grams and less expensive than a large portion of alternate bits accessible in the business sector. It is inserted with ATMEGA128 microcontroller, which contains 8K of RAM and 128K of outer memory. It transmits at a recurrence of 2.4 GHz at the information rate of 250 kbps.

Ultrasonic sensors. Ultrasonic sensors use sound waves rather than light, making them ideal for stable detection of uneven surfaces, liquids, clear objects, and objects in dirty environments. These sensors work well for applications that require precise measurements between stationary and moving objects [4].

B Software

The executed framework utilizes TinyOs-2.1.2 and NesC. TinyOS and NesC: TinyOS [3], an open-source and event based working framework which was particularly intended to keep running in gadgets with restricted stockpiling and low computational power, for example, WSN hubs. TinyOS bolsters in various bit stages (e.g., TelosB, IRIS, MICAZ, and so forth.) and give environment to the advancement of utilizations. TinyOS was created in NesC stage which is itself an augmentation to C. It was streamlined to work with the restricted stockpiling of sensor hubs.

Azure IOT Hub. Azure IoT Hub is a fully managed service that enables reliable and secure bi-directional communications between millions of IoT devices and a solution back end. Azure IoT Hub also exposes a range of public protocols and extensibility such as AMQP 1.0 and HTTP 1.1, as well as MQTT via the Azure gateway protocol. What differentiates Azure IoT Hub from the many other services and platforms is its processing power, with the ability to process millions of events per second on your hot path by using an event processor engine. It can also store them on your cold path for analysis. IoT Hub retains the event data for up to seven days to guarantee reliable processing and to absorb peaks in the load.

VI. Methodology and Performance Enhancement

A. Methodology

Bins are equipped with a Sensor Node (Here, an IRIS Mote which has a communication range of about 40-100 m). It measures the level of garbage using an ultrasonic sensor attached to its GPIO pin. Sensing interval is a variable parameter (set to 1 second by default). These motes are rugged, lower powered, low cost devices that can last a week on an AA battery [5]. While deploying each bin we assign a static Geolocation against the device Id so as to eliminate the use and cost of installing a GPS sensor. So we have a network of garbage bins each equipped with such a sensor node which all send the data to a sink node. There are multiple such sink nodes which further relays the data to the gateway node which via means of a web service uploads the data to the cloud. [6] The application layer protocol used for uploading the data to the cloud is MQTT. Once the data is on the cloud machine learning techniques are applied on the sensor data and garbage level prediction is done. The data of the predictive analysis along with the data about the current status of the garbage bins is sent to the client app. In the app pickup schedules are generated based on the obtained data. The pickup schedule is determined on the basis of certain eligibility settings that has been set up for the bins [2]. The eligibility setting are as follows:

a) Non Eligible: A state when the garbage bin need not be visited for collecting the garbage.

b) Eligible: All garbage bins in this state when a waste collection activity is on-going ought to be considered also for waste accumulation.

c) Critical: This is a state when the garbage been needs to be urgently visited for waste collection.

d) Minimum number of bins allowed per collection: 5 bins.

The threshold is defined 0-64% for the Non-Eligible state, 65-89% for the Eligible state and 90-100% for the Critical State.. Based on the pickup schedules the admin can direct the garbage collection vans along the shortest path consisting of all the filled dustbins that is again generated by the mobile app.

B. Mobile Client

There is also a client app to ease the task of deploying the bins as well as finding the shortest route comprising of all the filled bins. The client app is a Universal Windows App and has been programmed in C#. It consists of two modes namely the User mode and the Admin mode. The admin has the right to add the bin that he deploys by clicking on 'Add a Device' button and entering a Device Id. It can then monitor the filled level of the bin in the locality, the energy level of the microcontroller attached to each of the bins, reports about failures of a certain node in the network via the app. The user on the other hand can only view all the bins that has been deployed in the

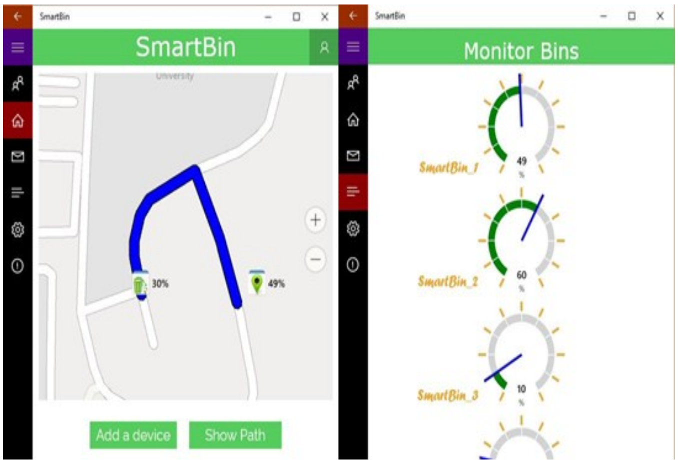

Fig. 4. a. Shortest path b. Filled level of garbage Bins

area by entering the area code that has been set up by the admin. The icons in the map indicates the various positions in which the bins have been deployed. We are using Bing Maps API to show the geographical location of the bin. Currently, the GPS coordinates has been set manually at the time of installation and triangulation techniques to automatically detect the location of the bin have not been used. The Admin can also get the shortest path comprising of all the filled bins by clicking on the 'Show Path' button as shown in Fig. 4. (a) and he can redirect the garbage collection vans along that path. For finding the shortest path Bing Maps Routing Engine has been used. The user can also monitor the Garbage level if he navigates to the Gauge Page where we have a gauge for every bin. The gauge displays real time data streaming in, updated every second as shown in Fig. 4. (b).

The idea of an intelligent, independently learning machine has fascinated humans for decades. At present, Billions of IoT devices are generating massive amounts of data from sensors, wearable devices, and other technologies. The amount of data generated is getting into the petabyte range, and increasing as more sensors become connected to the IoT. But it's not enough to simply collect the data; organizations need to analyze and make sense of it, recognizing specific patterns that can be utilized. That is where machine learning can play such a powerful role. Making the data actionable is where real value lies.

There are various places where machine learning is being used with IoT. Recently, a company called Prelert teamed up with a major metropolitan city to help solve its traffic congestion issues and become a 'Smart City' by studying patterns within its data. [1] The city deployed various sensors to collect information about travel times of cars, buses, accidents, construction zones, and various other data points that impact congestion. In our case, we are applying machine learning to the data leveraged by the bins to get useful insights, which can help in improving the efficiency of the garbage monitoring system.

Decision Forest Regression

Decision tree is a non-parametric model that perform a sequence of simple tests for each instance, traversing a binary tree data structure until a leaf node (decision) is reached. Random forest regression model consists of a collection of decision trees. [12] Each tree in a regression decision forest outputs a Gaussian distribution by prediction. An aggregation is performed over the collection of trees to find a Gaussian distribution closest to the combined distribution for all trees in the model.

Modelling the Sensor Network

Since sensor data from leveraged from the sensor is stored in Azure SQL database, a Decision Forest Regression model is created in Azure ML which trained using sensor data from Azure SQL database. After the model is trained and saved, a predictive web service is set-up. After the setup, the trained model is deployed as a predictive web-service.

An Azure Machine Learning web service can be consumed in two different ways

1) Request-response service

2) Batch execution service.

When deployed as a web service, the functionality is provided through the RESTful web service API. The web service can then be consumed in web sites, dashboards, and mobile apps. This is because the simple REST API accepts and responds with JSON formatted messages. In our case, we have used Batch Execution Service mode since

1) We need to periodically retrain the machine learning model underlying the web service.

2) Batch Execution service can handle asynchronous, high volume requests.

3)We are getting records of training data from Azure SQL database, which is supported by Batch Execution Service.

For IoT Devices we frequently need to retrain the initial model as new data is generated. Azure Machine Learning provides Programmatic Retraining API which helps us to retrain the model and update the Web Service with the newly trained model. [12] The 'DateTime' Field contains the datetime stamp at which the data is collected. It is parsed into Day of week, Day of Month and Month fields to create better features for training. Each of the generated field is of numeric type. "Location" field contain the location of smart-bin which sent the data. This field will only contain specific values i.e. the places where smart-bin is deployed.

'Level of Garbage' field will contain the level of garbage in the bins, which can be divided into three classes (Non-eligible, eligible, critical) based on percentage range [2]. Using machine learning we are learning patterns of filling of smart-bin at different places and at different points of time. For getting predictions, a query(s) is(are) created containing values for all fields except the class field.

For example- 2004-05-23T14:25:10, Rohini (New Delhi)

In JSON

{
"DateTime": "2004-05-23T14:25:10",
"Location": "Rohini (New Delhi)"
}

The query(s) is(are) stored in Azure SQL table. When the SQL table containing query(s) is(are) passed to the web service via REST API, we will get prediction(s) about the Level of garbage (0-100) pertaining to the field values from the SQL table. The predictions will be stored in Azure SQL table.

The predictions can be then fetched from Azure SQL table and can be used to get insights about the filling patterns of bins. The patterns can be visualized in the dashboard for better decisions. Predicting the patterns of filling of smart-bin can be used to design the routine check policy and pre-allocating/deallocating resources to bins which getting filled rapidly/slowly.

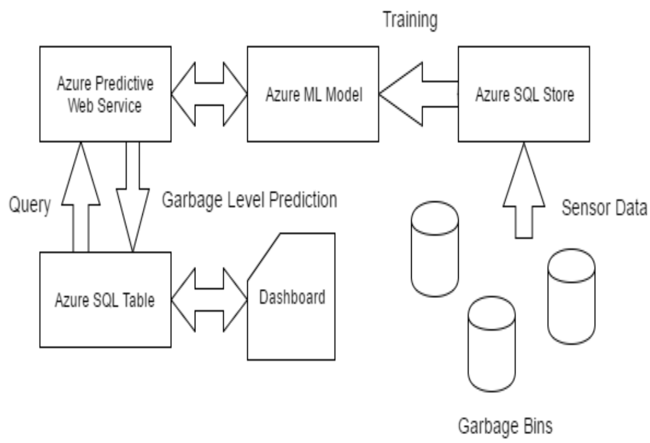

Fig.5. Workflow of the entire process of applying machine learning techniques to enhance the performance of the network of garbage bins.

Advantages

At the point when everything the world over is moving itself to innovation, then why not the dustbin? Dustbin is a fundamental part of the cleanliness mission and along these lines should be cared for well. The present strategy being taken after for waste gathering has numerous blemishes in it so a prompt stride must be brought before it breaks the entire system. Adding intelligence to our dustbins will solve most of our problems and the smart-bin has a lot of advantages. The product which is designed to make every dustbin smart is very handy as it can put to work just by placing the sensor ZigBee integrated model in the bottom of closing lid of dustbin. The first major advantage of it is that it will stop the menace of overflowing bins along roadsides and localities as smart bins are managed at real time. The filling and cleaning time of smart bin will also be reduced thus making empty and clean dustbins available to common people. Using the prediction and route algorithm it will smartly find the shortest route thus reducing the workforce, the number of trucks required to clean, the amount of fuel consumed by trucks and thus can save a large amount of tax payer's money as well. It also aims at creating a clean as well as green environment, as it will reduce the fuel consumption and in turn reducing the pollution in the air. Our work is a step towards such green technology.

VII. Conclusion and Future Work

In this paper we have shown the integration of Wireless Sensor Network with the Internet of Things using the Stack based Front End method using a test bed of a network of Garbage Bins. We discussed the various integration approaches and discussed how the Stack based Front End approach is suitable for this particular application. We also discussed how machine learning techniques can be applied to such a system and how a Decision Forest Regression model can be helpful to enhance performance of such a system. Presently this system has been tested in a very limited scale and using communication technologies that are not viable for city wide deployment of such a system. In future we would work upon implementing such a system using LPWAN communication technologies such as LoRaWAN (Long Range Wide Area Network) that are built for transmitting small chunks of data over long distances consuming very less power and forms a network that is scalable and thus is a good fit for successful deployment of such a system in wider area .

Refrences

[1] Narayan Sharma, Nirman Singha, Tanmoy Dutta, Smart Bin Implementation for Smart Cities, International Journal of Scientific & Engineering Research, Volume 6, Issue 9, September-2015, pp. 787-791.

[2] Samuel Idowu, Nadeem Bari, A Development Framework for Smart City Services, Lulea University of Technology.

[3] Tony Ducrocq, Michael Hauspie, Natalie Mitton, Balancing Energy Consumption in Clustered Wireless Sensor Networks, ISRN Sensor Networks, Volume 2013 (2013).

[4] D. Estrin, R. Govindan, J. Heidemann, and S. Kumar, BNext century challenges:Scalable coordination in sensor networks, in Proc. 5th Annu. ACM/IEEE Int. Conf. Mobile Comput.Netw., 1999, pp. 263– 270.

[5] Vikrant Bhor, Pankaj Morajkar, Amol Deshpande, "Smart Garbage Management System", International Journal of Engineering Research & Technology (IJERT), Vol. 4 Issue 03, March-2015Microtronics Technologies, "GSM based garbage and waste collectionbins overflow indicator", September 2013.

[6] Hindustan Embedded System, "City Garbage collection indicator using RF(ZigBee)andGSM technology".

[7] B. Chowdhury and M. U. Chowdhury, "RFID-based real-time smart waste management system," in Telecommunication Networks and Applications Conference, 2007. ATNAC 2007.

[8] V. M. Thomas, "A universal code for environmental management of products,"Resources, Conservation and Recycling, vol. 53, no.7 pp.400 –408,2009

[9] B. N. Clark, C. J. Colbourn, and D. S. Johnson. Unit disk graphs. Discrete Mathematics, 86:165–177, 1990.

[10] R. Roman and J. Lopez, "Integrating Wireless Sensor Networks and the Internet:ASecurity Analysis," Internet Research: Electronic Networking Applications and Policy, vol. 19, no. 2, 2009.

[11] C. Alcaraz, P. Najera, J. Lopez, and R. Roman, \Wireless Sensor Networks and the Internet of Things: Do We Need a Complete Integration?", 1st International Workshop on the Security of the Internet of Things (SecIoT10), pp. xxxx, 2010.

[12] A. Criminisi, J. Shotton, and E. Konukoglu, Decision Forests for Classification,Regression,DensityEstimation, Manifold Learning and Semi-Supervised Learning, Microsoft Research, 2011.

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