Gridifying IBM's Generic Log Adapter to Speed-up the Processing of Log Data

Claudi Paniagua  
IBM GTS, Virtualization and Grid Computing EBO  
SPGIT IMT IT, Barcelona, Spain  
cpaniagua@es.ibm.com

Fatos Xhafa  
Departament de Llenguatges i Sistemes Informàtics  
Universitat Politècnica de Catalunya  
Barcelona, Spain  
fatos@lsi.upc.edu

Thanasis Daradoumis  
Open University of Catalonia  
Department of Computer Science, Multimedia, and Telecommunication  
Rbla. Poblenou, 156. 08015 Barcelona, Spain  
adaradoumis@uoc.edu

Abstract

Problem determination in today's computing environments consumes between 30 and 70% of an organization’s IT resources and represents from one third to one half of their total cost of ownership. The first step to cutting down costs in this area and to enable autonomic computing systems is to have all parts of the system report status in a common log data format and semantics in order to be able to exploit the status information of the system as a whole. The Generic Log Adapter (GLA) is a generic parsing engine shipped with the IBM’s Autonomic Computing Toolkit that has been conceived to convert proprietary log data into a standard log data event-based format in real time. However, in order to provide generic support for parsing the majority of today’s unstructured log data formats the GLA makes heavy use of regular expressions that incur in performance limitations. Until now all the approaches that have been proposed to increase GLA’s performance have revolved around fine-tuning the set of regular expressions used to configure the GLA for a particular log data format or writing specific parsing code. In this work we propose a very new approach consisting in transparently parallelizing the GLA by taking advantage of its internal architecture and the fact that structuring log data is a task that lends itself very well to parallelization. We present a master-worker strategy that “gridifies” the GLA efficiently in a completely transparent way for the user.

1. Introduction

The goal of problem management, as defined by the IT Infrastructure Library (ITIL) [3], the de facto global service management standard, is to minimize the impact of situations in the IT infrastructure that adversely affects the business and to prevent those situations by initiating actions to permanently correct their root cause.

Problem management in today enterprise information systems is not an easy task: troubleshooting IT problems in medium and large companies can consume anywhere from 30 to 70 percent of the company’s IT resources, however problem management is a critical task, for instance, outage costs per hour on business-critical information systems can range from thousands to millions of dollars [2].
One of the factors contributing to the difficulty of problem management is the multitude of different ways in which the different parts of an enterprise information system do report status. Log files are a common strategy for this, but even then a simple web-based business application may easily contain as many as 25 to 40 different log files, each one reporting status information using its own (often inconsistent) data format and semantics. Extracting out what’s going on in the business application as a whole from these fragmented and inconsistently formatted data sources is a time-consuming and error-prone manual process that is only done reactively and off-line after a problem has occurred in order to diagnose it. The disparity and lack of consistency in both the format and semantics of log data makes it more difficult to write management tools that ease problem determination; less, proactively monitoring and correlating this log data in real time in order to automatically identify problems as they happen (or even before they happen).

The goal of autonomic computing [4] is to provide open, intelligent, resilient systems with self-management characteristics. This sounds rather ambitious; however, there’s an evolutionary roadmap in order to get to autonomic computing. The first step is obvious: standardize log data format and semantics in order to enable the automation of problem management activities across the entire enterprise information system.

The Common Base Event (CBE) format [5] is IBM’s implementation of the WSDM Event Format (WEF) OASIS standard [6]. CBE is an XML based universal log data format defined in XML Schema that organizes log data in events. An event is defined as the occurrence of a situation of interest. Log data sources are supposed to report status information as a temporal succession of discrete events, i.e., occurring situations. In CBE each situation is represented as an XML document that has a structure based on a “3-tuple” format which includes: (1) the component that originates the situation, (2) the component that observes the situation, and (3) the data that describes the situation, including correlation information.

If we had the components of our enterprise information system logging data as discrete events in the CBE format we could then move to the next step in the roadmap to autonomic computing, that is, since autonomic computing depends on being able to monitor changes in state of each part of the system as soon as they occur we need to deploy a communications infrastructure that allows us to connect in real time CBE sources to CBE consumers such as correlation engines, problem management tools, autonomic managers, etc. that automate monitoring and problem management.

An Event Driven Architecture (EDA) [7] allows connecting event emitters to event consumers in real time without introducing any coupling between them and is extremely well suited for supporting powerful techniques for monitoring and problem management such as complex event processing [8]. The Common Event Infrastructure (CEI) [9] is IBM’s implementation of the main building blocks of an Event Driven Architecture and a fundamental piece of IBM’s autonomic computing architecture that mediates between the CBE emitters and the problem management and monitoring tools.

The conclusion we can draw is that once a common data model to represent situations is in place and a suitable communications infrastructure is deployed to flexibly and selectively deliver those situations to interested parties in real time, there’s no limit to the sophistication of problem management techniques and abstractions that can be constructed and self-managing systems become possible. Nonetheless, the whole thing depends on the log data sources publishing status information as dictated by the common data model.

Because there is no cost-effective way to change existing products and legacy applications or solutions to log data in the CBE format, the IBM autonomic computing architecture includes adapters to translate disparate existing logs to the CBE format. The IBM’s Generic Log Adapter (GLA) [10] is an implementation of such an adapter conceived to ease the transformation of existing log data to the CBE format in real time. We will call log data normalization the process of transforming existing log data to the CBE format. The GLA uses a rules-based approach to normalize log data.

In this paper we are concerned with the efficiency of processing log data introduced above. Indeed, the computational cost is the main obstacle to processing this data in real time [4] as it is very costly and due to this in real situations this processing tends to be done offline in order to avoid harming the performance of the logging application. But as it takes place afterwards the solution to the problem management definition in IT enterprises, it is not satisfactory solved. Certainly, sequential approaches for the processing of log data cannot overcome this problem due to the huge amount of data to be processed. Grid technology is increasingly being used to reduce the overall, censored time in processing data by offloading these computationally costly tasks from the computing elements running them onto the Grid. Computational Grids [11] have emerged as a way to offer large computing capacity for solving complex problems by coupling together heterogeneous resources through interconnection networks. Computational Grids are thus an attracting alternative for the problem of processing in real time or
in quasi real time large amounts of log data collected during the daily activity of IT enterprises. By considering a Grid-based approach for processing log data, we show the benefits of the Grid by offloading the online processing of log data onto the grid. Moreover, we show how a simple Master-Worker scheme sufficed to achieve considerable speed-up. We notice that our approach is generic and can be applied for structuring event log data in general.

The rest of the paper is organized as follows. In Section 2 we explain how the normalization of Log Data with IBM’s Generic Log Adapter is done. Section 3 presents some considerations about the performance of the Generic Log Adapter. Section 4 introduces how the problem of structuring log data can be parallelized using the Master-Worker paradigm to parallelize IBM’s Generic Log Adapter. Finally in Section 5 we give details on the implementation and in section 6 we present the most relevant results of this work.

2. Normalizing Log Data with IBM’s Generic Log Adapter

This section describes how the GLA is architected and how it processes log data sources to generate and output CBE instances [12] in order to get a general understanding.

The GLA is written in Java and is architected following a chain of responsibility design pattern [13] that chains five different types of components corresponding to the five different phases in which the GLA organizes the normalization of log data (see Fig. 1). These component types are in the order in which they are arranged in the chain:

i. the sensor component: this component monitors one log data source (i.e. a log file) reading it line by line as it changes. When the sensor has read a preconfigured number of new lines it passes them to the extractor component.

ii. the extractor component: this component receives a collection of lines from the sensor component and parses it to delimit the log record boundaries (i.e. a log record may span multiple lines)

iii. the parser component: this component receives a collection of log records from the extractor component and parses them to map each one to a set of CBE attributes;

iv. the formatter component: this component receives a collection of sets of CBE attributes from the parser component and for each one builds the corresponding CBE instance based on the attributes of the set, and

v. the outputter component: this component receives a collection of CBE instances from the formatter component and persists or sends them to somewhere else in the infrastructure, usually the CEI.

At runtime a component is an instance of a Java class. All GLA components implement the IComponent interface that defines methods for managing the component properties and for starting and stopping the component. The IComponent interface is furtherly extended by two additional interfaces, IContext and IProcessUnit. The IProcessUnit interface defines the handler method of the chain, public Object[] processEventItems(Object[] msgs), this method is implemented by each component in the chain to provide its specific processing.

![Figure 1: Architecture of the GLA](image)

The chain is managed and orchestrated by a context component, i.e. a component implementing the IContext interface. The remaining interfaces, ISensor, IExtractor, IParser, IFormatter and IOutputter extends the IProcessUnit interface to provide specific methods for each one of the sensor, extractor, parser, formatter and outputter components respectively (see Fig. 2 below).

The context component is a runnable (i.e. active) component that runs in its own thread the main log data processing loop for normalizing a particular log data source in real time. The loop’s step is depicted in Fig. 3, where the context component calls the ISensor’s method public Object[] getNext() which blocks until the configured number of new lines of log data is available and returns these; then the context component calls the IProcessUnit method processEventItems in each of the processing components in the order explained, passing as argument to the next call the results returned by the previous call.
The GLA provides default implementations for all these interfaces but it is also architected following a plug-in design that allows the user to plug custom developed components. In fact, the specific Java classes that conform a context (i.e. a chain of components) to normalize a particular log data source, together with their configuration parameters, can be specified using an XML file, called the adapter configuration file. The GLA takes this configuration file as an initial argument and instantiates the chain as configured. One can define more than one context in the same adapter file, thus the same GLA instance is able to normalize more than one different log data source.

The GLA ships with a very rich Eclipse [14] based development environment that allows to visually configuring contexts in a very user-friendly way, as well as to test and debug those contexts on sample log data (see [15]). The output of the development environment is an XML file (i.e. the adapter file) that you can use to instantiate a GLA instance that will transform the log data sources as described by the XML file.

3. Considerations of the Performance of the Generic Log Adapter

In this section we analyze some performance considerations regarding the GLA that later motivated our approach to parallelize it. We start by taking a slightly more formal look at the process of normalizing log data.

Log data normalization can be modeled using elements of formal language theory [16]. The log data generated by a log data source between two instants in time can be represented by a word (i.e. a string), $\omega$, from a given alphabet, $\Sigma$, that contains all the characters that the log data source may possibly use to represent log data. The sensor component then reads this word as it is being generated, thus outputs a sequence of sub-words of $\omega$, say, $\omega_1, \omega_2, \ldots, \omega_m$. The extractor component acts on these sub-words one at a time, outputting a collection of sub-words, $E(\omega_i) = \omega_i1, \ldots, \omega_{in}$, of $\omega_i$ each one corresponding to a different log record or message and thus verifying one simple but very important property: they are independent units of structure, that is, each one of these sub-words contains all the information the parser component needs to access in order to be able to map it into a set of CBE attributes, $P(\omega_{ij})$, that the formatter component will transform into a CBE instance, $F(P(\omega_{ij}))$.

Now we can see that to normalize a piece of log data $\omega_i$, we need to compute $F(P(E(\omega_i)))$ where $P(E(\omega_j)) = P(\omega_{j1})\ldots P(\omega_{jn})$ and $F(P(E(\omega_i))) = F(P(\omega_{i1}))\ldots F(P(\omega_{in}))$. Let’s roughly compare the relative time complexity of the computations $E$ and $P$ for the case of the default implementations for the extractor and parser components that come with the GLA [1]. Both implementations use regular expressions specified by the user at configuration time through the eclipse-based tooling, however, the way in which the two types of components use the regular expressions differ considerably and have direct implications in performance.

The extractor component default implementation uses two regular expressions, one to define the pattern that starts a new log record and another one to define the pattern that ends a log record. The extractor scans $\omega_i$ looking for these patterns, each time it finds a match it includes the characters that

---

1 The computation, $F$, that the formatter component performs is essentially different from $P$ and $E$ and thus cannot be compared. It boils down to creating $n$ CBE instances, $e_i$, and then filling it as specified by $P(e_i)$. 

follow into a new sub-word $\omega_j$ until it finds a match for the end pattern. On the other hand the sensor component default implementation uses an ordered collection of regular expressions for each CBE attribute that is to be filled from log data. It works as follows, for each sub-word $\omega_j$ for each CBE attribute to be filled and for each regular expression associated to the CBE attribute (in the order they were defined by the user) the sensor component scans $\omega_j$ looking for a match, if one is found the matching characters are used as the value for the CBE attribute and no more regular expressions associated to this CBE attribute are essayed for $\omega_j$. If no match is found the CBE attribute if left with an undefined value.

Now the time complexity of matching a regular expression in a string is directly proportional to (1) the length of the regular expression, (2) the complexity of the regular expression and (3) the length of the string. While the length of the string that the extractor and parser implementations need to scan is the same (i.e. $\omega_i=\omega_i,…\omega_n$), the extractor implementation only needs to essay at most two, usually very simple and short, regular expressions, while the sensor component needs to essay usually a large number of regular expressions that tend to be complex and lengthy [17]. This has serious implications for performance and is the reason why some attention has been put in suggesting how to write efficient regular expressions for the GLA [17,18,19].

Since the GLA’s main processing loop is a chain of synchronous calls that must all finish before the next iteration can start, the parser component becomes a bottleneck: this may not be a problem if log data is generated at a slower rate than that at which the GLA is able to process it, however if this is not the case a remnant of log data pending to be processed is accumulated introducing thus a delay that may even exceed the time between the input of the problem can be easily partitioned in these units of structure (i.e. individual log records) which means that if the problem is partitioned using the boundaries of these units no dependencies between tasks will exist, and the input of the problem can be easily partitioned in these units of structure since, as we have seen, these can be done using at most two simple regular expressions.

Given all the above, the GLA can be naturally parallelized using the MW paradigm by grouping the sensor and extractor components at the master side and leaving the parser, formatter and outputter components at the workers side, see Fig. 4.
The advantage of using MW approach is threefold. On the one hand we decouple the sensor and extractor components from the parser, formatter and outputter components, that is, in our approach the master’s main processing loop does not need to wait for the parser, formatter and outputter components to finish its processing, the extractor component just passes the collection of log records to some worker and returns immediately. The worker then performs the rest of the processing asynchronously in another machine. This effectively shortens the main processing loop at the master side, where the log data is being generated, to just the sensor and extractor components, thus increasing the rate at which log data sources are monitored for changes. On the other hand we are able to offload the bulk of log data normalization computation to machines other than the ones that are producing the log data, which usually require as much resources as possible for their production running applications. Last but not least, we are able to normalize log data in parallel thus speeding-up the processing and making it more real-time.

However it should be noticed that there’s a drawback on the approach: the master is not in full control of the size of the tasks that it sends to workers since log records can have arbitrary size and we do not control neither the rates at which log data sources do produce log data. This fact reduces the capacity of the master to play with the task size in order to better adapt to the different computational capacities of the workers and/or to their variable workloads, especially if the sizes of log records are too large or the log data generation rate is too low. In general we will be only able to play with the task size if the real time processing requirements are not very strict thus allowing us to accumulate log data of low volume log data sources until the task of the size is “big enough”.

We can conclude that a parallel implementation of log data normalization is applicable to high volume log data sources, but also to low volume ones provided that they have low real time processing requirements.

5. Transparent Parallelization of IBM’s Generic Log Adapter

In order to experimentally test the feasibility of the MW paradigm for parallelizing the normalization of log data we have implemented a minimal Grid prototype that parallelizes the GLA. We used the Globus Toolkit 3.2 and we deployed the prototype on the Planetlab platform. Both Globus Toolkit 3.2 and Planetlab are briefly described next.

The Globus Toolkit (GT) [29] is the actual defacto Grid middleware standard. Version 3 of GT (GT3) is a refactoring of version 2 in which every functionality is exposed to the world via a Grid service. Grid services are basically stateful web services. The core of the GT is a Grid service container implemented in Java that leverages and extends the Apache’s AXIS web services engine.

Planetlab [30] is an open platform for developing, deploying and accessing planetary-scale services. It is, at the time of this writing, composed of 726 nodes hosted in 354 different sites. Each Planetlab node is an IA32 machine that must comply with minimum hardware requirements (i.e. 1GHz PIII + 1Gb RAM) running the same base software, basically a modified linux operating system offering services to create virtual isolated partitions in the node, called slivers, which look to users as the real machine. Planetlab allows every user to dynamically create up to one sliver in every node, the set of slivers assigned to a user form what is called a slice. It is said that a Planetlab node can run up to 100 concurrent slivers.

In order to test our GLA grid prototype we turned Planetlab into a Grid by installing the GT3’s Grid service container in every sliver of our slice. Moreover, our objective was to transparently parallelize the GLA, that is, to allow users to run their adapter files unmodified on the parallelized GLA (PGLA). In order to achieve this we reused the GLA code to make two versions of it: the master GLA and the worker GLA. The worker GLA is a grid service that exposes a single operation akin to the original GLA handler operation processItemEvents but that also receives the adapter file as an additional argument to the array of log records to be processed. The implementation of this operation uses the original GLA code to instantiate the chain of components as specified by the adapter file, then a minor modification is introduced that allows the chain to be initiated in its own thread at the parser.
component, bypassing the sensor and extractor components. This is the only modification required to the original GLA code to implement the worker GLA. In other words, the worker GLA executes exactly the same java bytecode (except at initialization time) to process the log data as the original GLA. This makes very easy and consistent the performance comparison between the sequential and parallel approaches. We deployed the worker GLA grid service on the GT3’s containers of every sliver of our Planetlab slice.

On the other hand, the master GLA is again the original GLA code with a minor modification that forces the instantiation in the chain of a proxy component in between the extractor and parser components and modifies the chain execution so that only the third first components are called, that is, the sensor, extractor and proxy components. The proxy component reads in its `processItemEvents` from a configuration file the available GLA worker services method and implements a simple list scheduling strategy to forwards calls to the worker GLAs by invoking the corresponding grid services. This is a very simple scheduling strategy but notice that our objective was not to create a full-blown GT3-based MW implementation of the GLA but rather to show the feasibility of a transparent parallel Grid-based implementation of the GLA using the MW paradigm minimizing the amount of code to be modified from the original GLA.

6. Conclusions

In this paper, we first have motivated the need to structure and process in real time the large amount of information generated in IT enterprises. The problem of structuring and processing log data is gaining importance due its usefulness in problem determination, which is shown to be very costly and needing time superior to that of a single computer or of LAN of computers. We have considered the case of IBM's Generic Log Adapter and shown how to use a grid-based approach to efficiently speed-up the processing of log data. Although we have particularized our approach for the IBM's Generic Log Adapter, our approach is applicable in general to the structuring and processing of log data [26].

Thus, our results show the feasibility of parallelizing the problem of structuring any plain text event log data, achieving considerable speed up, provided that (1) the normalization algorithm’s running time function, \( f(n) \), be of strictly upper order than the transmission time function, \( n/B \), that measures the time required to transmit a piece of data of size \( n \) for a bandwidth \( B \) (i.e. \( f(n) = o(n/B) \) ), and (2) the log data can be easily parsed (i.e. with few and simple regular expressions) in order to be broken in independent units of structure (i.e. log records). These conditions are expected to be satisfied by both log data and structuring algorithms, especially the ones that can be found in generic log data structuring/normalizing frameworks such as the GLA which are implemented using regular expressions.

Acknowledgments

This work has been partially supported by the Spanish MCYT project TSI2005-08225-C07-05.

7. REFERENCES

3. IT Infrastructure Library, http://www.itil.org
22. Felix Salfner, Steffen Tschirpke, Miroslaw Malek, Humboldt-University Berlin (2004) Comprehensive Logfiles for Autonomic Systems. 18th International Parallel and Distributed Processing Symposium (IPDPS'04) - Workshop I1
24. Using the Generic Log Adapter with the Log and Trace Analyzer, developerWorks Tutorial
25. John P. Rouillard, Real-time log file analysis using the Simple Event Correlator (SEC), 18th Large Installation System Administration Conference (november 2004)