Self-Aware Services: Using Bayesian Networks for Detecting Anomalies in Internet-based Services

A. Bronstein, J. Das, M. Duro, R. Friedrich,
G. Kleyner, M. Mueller, S. Singhal
Hewlett-Packard Company
1501 Page Mill Road
Palo Alto, CA 94304
{alex_bronstein, joydip_das, marsha_duro, rich_friedrich, gary_kleyner, martin_mueller, sharad_singhal}@hp.com

I. Cohen
Beckman Institute
405 N. Mathews Ave.
Urbana, IL 61801
iracohen@ifp.uiuc.edu

Abstract

We propose a general architecture and implementation for the autonomous assessment of health of arbitrary service elements, as a necessary prerequisite to self-control. We describe a health engine, the central component of our proposed 'Self-Awareness and Control' architecture. The health engine combines domain independent statistical analysis and probabilistic reasoning technology (Bayesian networks) with domain dependent measurement collection and evaluation methods. The resultant probabilistic assessment enables open, non-hierarchical communications about service element health. We demonstrate the validity of our approach using HP's corporate email service and detecting email anomalies: mail loops and a virus attack.

Keywords

Service management, anomaly detection, Bayesian networks, fault and performance management.

1. Introduction

Managing complex hardware and software systems has always been a difficult task. The Internet and the proliferation of web-based services have increased the importance of this task, while aggravating the problem in at least four ways:

- Internet speed software development and release means less reliable and more frequently updated software.

- Multi-tier and distributed software architectures increase the complexity of the environment and obscure causes of both functional and performance problems.
- Internet style service construction implies more dynamic dependencies among the distributed software elements of the overall services making it difficult to construct and maintain accurate system models.
- Internet scale deployments increase the number of service elements under a particular administrator's responsibility.

Currently, the paradigm for detecting problems in computing environments is to monitor many hardware, software and system operational variables across time and note the occurrence of abnormal events. The information is typically monitored by small sets of network, system and application administrators who assess, for each service element, whether that element is 'healthy' or not. In this context, the assessment of health is a determination of whether the current observed behavior is consistent with expectations. These expectations may be based on models of correct behavior or on observations over time and the patterns within those observations. The assessment of health is key to troubleshooting problems and detecting faults and failures before they propagate to the users of the system.

As the numbers of service elements and complexity of service environments have grown, so has the amount of management information, increasing the burden on IT staff. Advances toward more efficient and accurate problem detection have included:

- Applying reasoning techniques to the monitoring information to help the administrator answer the question 'is this service element healthy?' Simple examples include the commercially pervasive use of fixed or statistical thresholds and the classification of alarm levels. Commercial applications of more sophisticated reasoning technology, for example, neural networks [1], are also beginning to emerge.
- Applying reasoning techniques to the abnormal events information to help answer the question 'which service element is causing the problem?' Alarm or event correlation systems [2] are now found in many commercial products [3] [4] [5]. Rule-based or model-based expert systems associate individual abnormal events with service elements, and group events to focus on the likely causal element(s), thereby reducing the set of events that need to be presented to the administrator.

Sophisticated anomaly detection technologies are now seen in the network management and hardware management spaces. Anomaly detection in software, however, has made less progress. The advent of complex, distributed and federated services has brought a new class of challenges.

In the research community, attempts have been made to extend existing management models to include service elements as first-class objects, such as [6], [7] and [8]. In the probabilistic reasoning arena [9], Hood [10] [11] [12] has used a Bayesian network over threshold violations in measurements in a computer network to give a probabilistic assessment of the existence of a fault in the network. Our work builds on these approaches, by generalizing Hood's Bayesian network application idea to arbitrary service elements.

The rest of this paper is organized as follows: in section 2, we present the model and architecture for self-aware services, and its properties. In section 3, we describe an instance of that architecture, customized to email services and detection of mail loops and virus intrusions. Finally we summarize our contributions and discuss directions for future work.

2. Self-aware services

2.1. Motivation: self-awareness of health as a management paradigm

A complex service can be viewed as a set of interdependent service elements or objects. Managing such a service, from the point of view of detecting anomalies in its functioning and locating the responsible sub-service elements, is a difficult task. The motivation underlying our work is that such tasks become easier when service elements are aware of their own health. In the ideal case, all service elements, at all levels of abstraction, are able to accurate assess and efficiently communicate their health status, at all times. Anomaly detection becomes trivial, and fault localization becomes simpler.

This vision leads us to propose that all service elements be equipped with machinery, logically local to each element, that accurately and sensitively evaluates the element's health. The resulting distributed health assessment architecture can then begin to address the scalability issues brought on by the Internet.

Basing the health evaluation on statistical deviations from past history obviates the need for precise models of the service element's behavior. Statistical evaluators, by using time dependent weighting, can adapt to dynamic changes in the service elements. This model independence and dynamic adaptability are advantageous in the context of complex and dynamic architectures, as well as high software churn.

Allowing model-based health evaluations within the same architecture gives us the potential for higher accuracy, when those models are available.

In addition, we believe that much of the machinery needed to compute and communicate service element health can be made largely independent of the specific element and its semantic domain. This is the basis for proposing a general architecture, whose instances are customized to a wide variety of service elements.

We define 'self-awareness' as the ability of an element to autonomously detect deviations in its behavior that are meaningful. We define 'self-control' as the ability of the element to respond to this information in a manner that appropriately changes its behavior. Accurate self-awareness is prerequisite to self-control, and in this paper, we will focus on the self-awareness aspect of the overall vision.

2.2. Health engine: sensing, evaluating and Bayesian reasoning

The computation of a single, accurate, assessment of health is key to the expected benefits of this work. We therefore explain the logical model of the health engine in detail below.

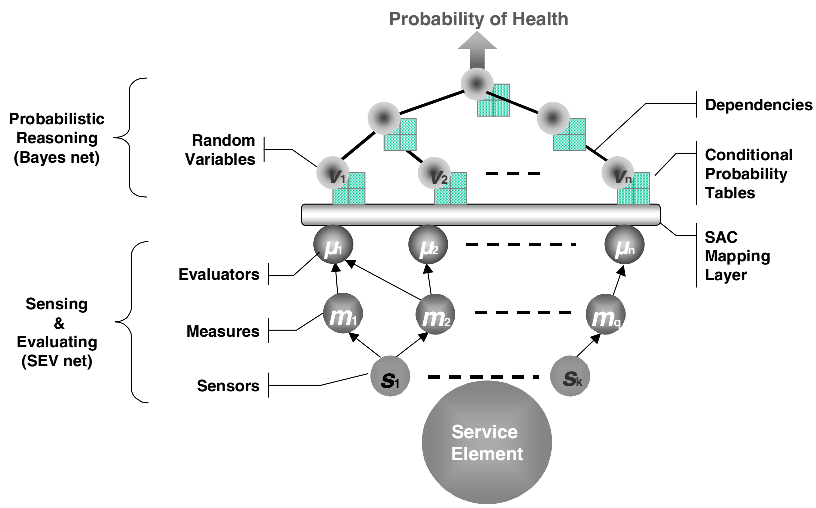


Figure 1: Health Engine Model

The health engine achieves its result by first logically wrapping 'sensors' around a particular service element. Those sensors generate measurements over time, which are stored in the 'measures'. We use the terms, sensor and measure, in a broad sense, intended to denote any information capture about the behavior of the underlying service element. Sensors may or may not require cooperation from the underlying element. Examples of cooperation-independent sensors are operating system tools that measure CPU usage, memory consumption, or I/O rates for a particular process. Alternatively, calls to management APIs of a service element (if they exist) are cooperation-dependent sensors in our terminology. Another useful and commonly available sensor is an application log parser/analyzer. For abstract service elements that do not correspond to a single process, active tests by pseudo-clients can be constructed as sensors in our framework. Where warranted, sensors that intercept the request/response flow of the underlying element also fit within the architecture.

The second layer in the health engine accumulates the information provided by the sensors in the measures. The architecture allows for information of any type to be stored there. The amount of past data to be kept is measure specific. A given sensor can contribute data to one or several measures; we denote that information flow with arrows going from the sensors to the measures in Figure 1.

The next layer is the 'evaluators'. These are functions that process one or more of the measures, to yield an opinion of the service element's health. The opinion can be expressed in binary, tertiary, or any N-ary form. The evaluators have access to a statistical library and a time-selection construct, so that 'within 2 standard deviations of the mean value in the last 30 days' can be expressed easily. The evaluators are not limited, however, and are free to exploit domain constraints either in the data extraction phase or in their statistical computation.

The top layer attempts to subtly combine the individual opinions expressed by the evaluators into a single assessment, using knowledge about the accuracy of the evaluators in different circumstances. The intuition here is that reasoning about the evaluators' opinions yields more accurate conclusions than simply 'ORing' them, as is commonly done. In our first implementation, we chose Bayesian networks in the top layer for several reasons. Bayesian networks are a proven technology in the field of diagnostics [13] [14] and are capable of leveraging prior expert opinions with learned information from data [15].

The individual health evaluations are entered as evidence (in the Bayesian reasoning sense) to the Bayesian inference engine. The customized Bayesian networks are specified to have one leaf node ('random variable') for each evaluator. The conditional probability tables encode how much weight to attach to the opinion of each evaluator. The Bayesian inference engine always functions on partial evidence, so an evaluator unable to give an opinion for any reason (e.g. lack of sensor data) does not require special treatment. Whenever an assessment of the overall health is needed, the current evaluations are entered as evidence, and the inference engine computes the resulting probability for the top node. The probability is the single assessment of health at that instant.

2.3. Expanding the semantic range of health communications

Management systems typically communicate information about element health via lists of name-value pairs (e.g. MIB readings) or notifications of abnormal events (e.g. SNMP traps). Those information types are understood only by a management overseer or monitor. By providing reduced and universal information about health (a real number between 0 and 1), and communicating via broadly accessible mechanisms (XML + HTTP), we enlarge the pool of possible applications that can communicate about a service element's health to:

- a variety of management applications beyond the top monitor;
- a peer, such as a potential customer or supplier of that service element;
- the service element itself! (Hence the name 'Self-Aware Services'…).

A frequent issue in distributed management systems is the need to standardize the language used for communicating information between service components and the management system. In our architecture, the basic information about health has been reduced to a single number and can thus be communicated using any existing language that allows tagged variables.

Although we believe that there is value in reifying the concept of element health and reducing it to a single number, we recognize that there are drawbacks. To address some of these, the architecture places no restrictions on additional information that could be communicated. For example, in the implementation we will describe later, we defined in our XML an additional 'Details' tag which allows for the inclusion of CIM-XML reports or dumps from evaluators and sensors. Further, we have anticipated the possibility of different definitions of health by not restricting the number of Bayesian networks that can be used simultaneously. This is useful in cases where applications belong to significantly different semantic domains and need to communicate different notions of health.

2.4. Self-awareness architecture

Our proposed self-awareness architecture therefore rests on three ideas:

1. We generalize the measurements and thresholds concept widely found in commercial system management technology to a collection of sensors for measurement capture, measures for relevant measurements accumulation, and evaluators for the generation of opinion about the service element health, based on statistical or absolute tests.
2. We combine the multiple opinions about the element health into a single, probabilistic assessment, using probabilistic reasoning technology.
3. We communicate using standard web technologies. To configure the engine and communicate the health information to other service components and/or management systems, we use open XML-based descriptions transported over HTTP.

These fundamental components of the self-awareness architecture are depicted below, in Figure 2.

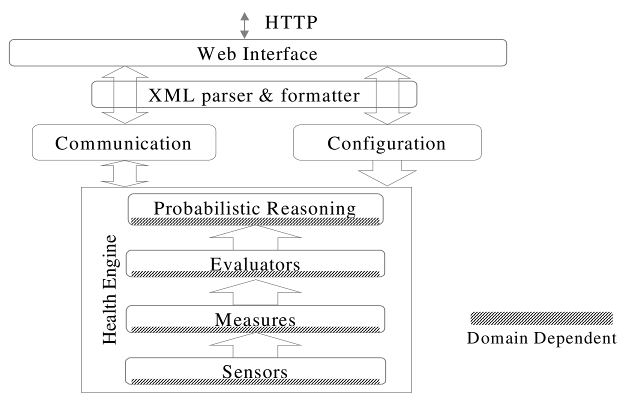


Figure 2: Health Awareness Architecture

The resulting health assessment can be fed into existing management systems to assist administrators, or into higher-level fault localization systems, such as event correlation systems. It can also be passed to a local control module for the service element itself, thereby yielding the ‘Self-Awareness and Control’ paradigm.

While largely domain independent, in implementation, the machinery is tailored to a domain by configuring a Bayesian network, and a set of associated Java classes for the element specific parts of the sensors, measures and evaluators.

2.5. The generality of the technology

The SAC architecture and machinery are general: the overall communication mechanism and SAC framework are element independent. The Bayesian network engine, and many of the mechanisms for accumulating and processing the measurements are element independent.

Semantically, there are no restrictions on the kind of service element to which the SAC concept can be applied. The application of this architecture to a service element involves customizing the sensors, picking meaningful measures, and defining appropriate evaluators for the health question at hand. Further, the parameters of the Bayesian network, that is, the conditional probability tables must be specified, reflecting any prior knowledge about the behavior of the service element.

The practical granularity of the service elements that can be made self-aware is constrained only by the resource footprint of the implementation and the resource budget of the domain.

3. Experimental validation

3.1. Virus and mail loops detection using SAC

To test the validity of the SAC approach, we have implemented this architecture a number of times, each time adding more capability. We used HP Chai [16] [17] in our first prototype as the front end web server because it provided us with a lightweight web server which is designed to allow back-end servlet applications to be integrated easily. Any other web server and servlet facilities could have been used. For the Bayesian engine, we wanted a lightweight and memory efficient engine and used Professor Fabio Cozman's EBayes [18], intended for embedded environments. The Bayesian networks were described in an XML dialect: XBN [19], slightly extended to include the linkage between the Bayesian network nodes and our evaluator class names. We used an XML parser available from IBM [12].

Abstract Java classes provide a large part of the functionality needed for building sensors and evaluators. To customize a SAC to a service element, small concrete Java classes that gather and rate relevant information are defined and written. Those classes can leverage all the functionality provided by the abstract parent classes, as well as the statistics and time selection libraries. In the experiment described below, we modified 7 Java classes, out of the more than 70 we have coded into the framework. We also coded a logfile parser, specific to this experiment.

Most recently, we applied the SAC concept to the detection of a set of email anomalies on a corporate mail system. In this experiment, we attempted to detect a virus infection with no knowledge of the specific attributes of the virus. We also attempted to detect mail loops, as these also negatively impact mail systems, principally by increasing traffic and thereby using system resources. Mail loops often go undetected by email monitors unless the load becomes excessive or the administrator catches the traffic by chance.

The source of information, the sensor in SAC terminology, was the mail (postfix) logfile from a corporate firewall that handles messages going in and out of the HP domain. This firewall does not see any internal email traffic. Virus detection at this level is more difficult because the intensity of the virus-induced traffic is lower at this corporate boundary than in the internal mail system. Most recent email viruses use the user's address book to send themselves out, and most address books in a company contain principally internal email addresses.

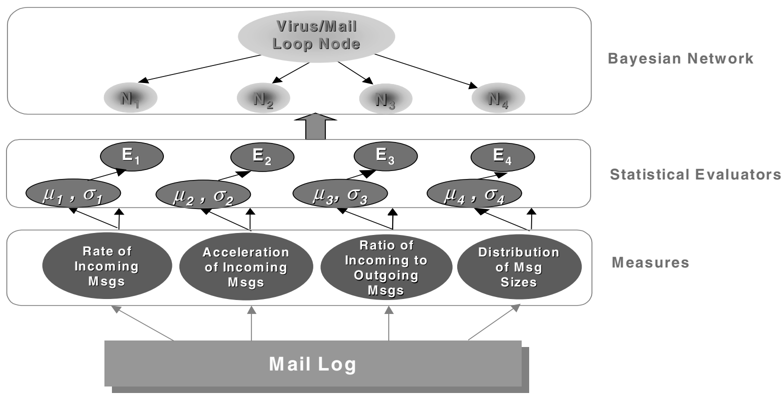


Figure 3: Structure of the Virus/Mail Loop detector

Figure 3 shows the structure of the system, including the structure of the simple Bayesian network. The measures and evaluators were chosen based on conversations with an experienced member of the corporate email support organization. His input was also used to set the parameters of the conditional probability tables, reflecting how much the particular evaluator should be trusted to indicate the presence of the targeted mail anomalies.

3.2. The sensors and measures

The mail logs record every action taken by the mail system: when a message is received, from whom and to whom, the message size, when there is an attempt to deliver a message, and the status of the attempt ('sent', 'deferred' or 'bounced'). From the logs, four measures were computed:

- The rate of received messages. The rate was defined to be the number of incoming messages observed in the measurement interval, divided by the interval size, 10 minutes in all of these experiments.

- The acceleration of the received messages. The acceleration was defined to be the difference in the above rates over two consecutive intervals, divided by the interval size.
- The distribution of incoming message sizes. The frequency distribution of message sizes was accumulated and the bin contents normalized by the total number of messages observed in the interval. The measure was the magnitude of the peak bin, a value between 0 and 1. When a virus outbreak and email loop occurs, there is a spike around a particular message size. This has been observed in the recent virus outbreaks. This measure picks up mass emails as well, but the next measure offsets this drawback.
- The ratio between the incoming messages and outgoing messages over the measurement interval. This measure was defined to be the absolute value of the difference between this ratio and 1. Viruses and mail loops emails usually have one recipient per email message. In an outbreak, this ratio comes closer to 1 than during normal operation.

For this experiment, the subset of possible measures chosen was small and not specific, by intent. Many current virus detection systems rely on text strings being present in the virus (e.g. 'Life stages' in the subject line). New viruses can bypass these detection systems simply by changing text strings. Our implementation did not depend on a specific pattern in the virus itself, but on the effect the virus has on the mail system, namely the change in traffic characteristics that occurs when a virus is present. This allows us to detect the virus in a more virus independent manner.

3.3. The evaluators

The SAC architecture neither specifies nor restricts the type of evaluation applied to the measures. In this experiment, we used simple statistical evaluators, namely the mean *(μ)* and standard deviation *(σ)*, computed over the last 2 hours, to determine whether the measures indicated a problem. We chose these evaluators with no implied assertions about the underlying statistical characteristics of the measures.

The values of the evaluators for the incoming message rate, acceleration and the message size peak were determined as follows:

$$\text{Evaluator} = \begin{cases} \text{Good} & \text{if present Measure} \le \mu + \sigma \\ \text{Medium} & \text{if } \mu + \sigma < \text{present Measure} \le \mu + 2\sigma \\ \text{Bad} & \text{if present Measure} > \mu + 2\sigma \\ \text{Don't Know} & \text{if no past measures were available to compute } \mu \text{ and } \sigma \end{cases}$$

The evaluator for the ratio of incoming and outgoing messages was determined by:

$$\text{Evaluator} = \begin{cases} \text{Good} & \text{if present Measure} \geq \max(\mu - \sigma, \frac{\mu}{2}) \\ \text{Bad} & \text{otherwise} \\ \text{Don't Know} & \text{if no past measures were available} \end{cases}$$

The above illustrates the ability of the Bayesian networks to handle 'Don't Know' as an input from any evaluator.

3.4. The experiment

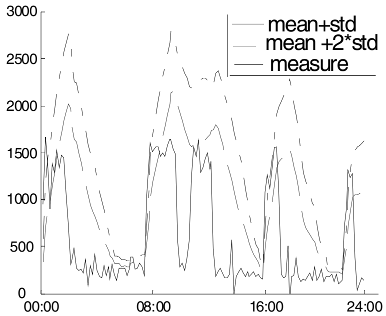
For this feasibility experiment, 17 days worth of mail logs from one of the firewall systems were analyzed. During this period, one notably virulent attack occurred ('Life stages' virus) and affected the system for approximately half a day before defenses were installed. Over 200 of the more than 2400 measurement intervals were impacted by significant mail loops, as established by a combination of manual log observation and automated counting by a script. This data sample was deemed a good test bed for the SAC since it had enough adverse events to enable a meaningful statistical evaluation. The experiment we describe was done offline to allow a detailed statistical analysis of the output of the system. This was an implementation choice, consistent with the research objective, not a limitation of the architecture. A real-time version is under development.

3.5. Results

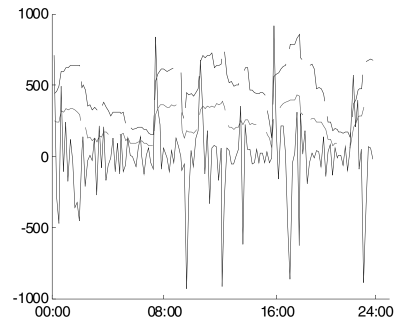
The effects of combining the outputs of several evaluators with a Bayesian network are illustrated in Figures 4 and 5. The individual evaluator graphs show both random as well as systematic variability in the individual measures. Each of the four sub-figures plots one of the four defined measures, as a function of time for one 24-hour period in the 17-day experiment.

Predictable spikes, at the beginning and the end of the business day, are seen. Other, less readily explained, order of magnitude variations in the individual measures are present. The variability of these data illustrates the impracticality of using static thresholds as alarms.

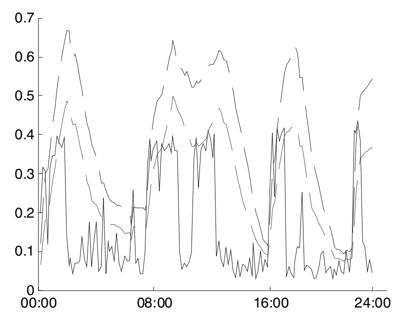
Superimposed on these sub-figures are plots of the decision boundaries where the statistical evaluators registered 'medium' or 'bad'. In sub-figures (a)-(c), corresponding to the incoming message rate, acceleration and peak message size measures, the dashed lines correspond to the recently time-averaged means plus one and two standard deviations. For the fourth measure, the ratio of incoming to outgoing messages, only one decision boundary was defined and hence shown.



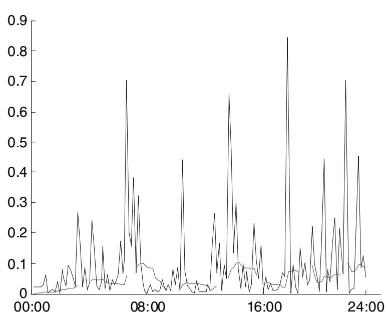
(a) Incoming message rate



(b) Incoming message acceleration



(c) Peak of message size distribution



(d) Ratio of incoming and outgoing messages

Figure 4: Plot of the measures for all 10 minutes periods of one particular day with the decision boundaries of the evaluators

In Figure 5, we display the output of the Bayesian network, corresponding to the probability of the email anomaly over the same 24-hour measurement period. The apparent improvements in signal differentiation and noise attenuation were validated and substantiated by statistical analyses using standard detection evaluation techniques that we describe next.

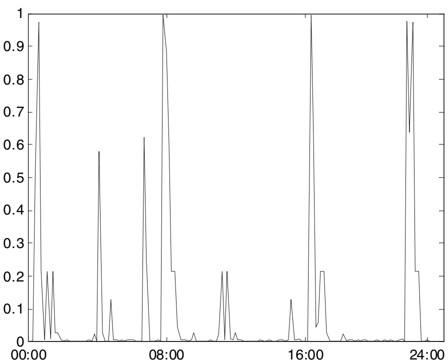


Figure 5: Probability of virus or mail loop, computed over the same 24 hour period as Figure 4

To validate the output of the Bayesian network, we used a detection evaluation method called the Receiver Operating Characteristic (ROC, extolled in [20]). The ROC is a graph showing the probability of accurate detection of an event versus the probability of a false alarm, using a moving decision threshold. In our case, the decision threshold is applied against the output of the SAC. The upper left point (0,1) denotes the ideal of complete detection with no false alarm. In general, the closer the curve comes to that point, the better.

Another useful evaluation of the detector plots the probabilities of error as a function of the decision threshold. The range of thresholds that yield optimal performance is indicative of robustness.

The computation of the ROC and error probability curves requires that we know the 'ground truth' in the experiment, that is, that we have a way of validating if a given detector output is correct or not. In any detection experiment using real-life data, the determination of the ground truth is a critical but often difficult task, which affects the reported performance. For determining the ground truth for the loops, we used a script that reconstructed the mail traffic from the log, looking in detail at the addresses of the senders and recipients. We filtered out all messages with more than one recipient and then counted all back-and-forth message pairs between unique sender/recipient pairs. We counted the mail loop traffic in each 10 minute interval and labeled as anomalous any interval with loop traffic in excess of 10% of the peak throughput of the server.

The performance results shown in Figures 6 and 7 are modest, consistent with a first attempt at defining evaluators appropriate for those anomalies. While evaluating the accuracy of the detector, we observed that the choice of adaptive statistical measures (moving averages) as evaluators made the detector sensitive to the onset of a problem, but insensitive to the ongoing presence of long lasting problems. For example, there was one intense mail loop that plagued the system intermittently for over three days. The SAC health probability dropped with the onset of the loop, but then recovered, despite the continuation of the anomaly. The evaluators adapted to the presence of the loop and no longer indicated a problem. The probability of miss curve displayed in Figure 7 is significantly impacted by this edge detection effect.

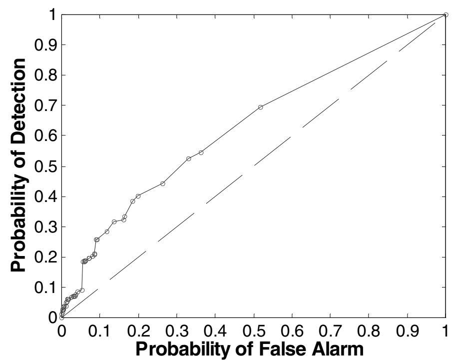


Figure 6: ROC of the experiment (solid line)

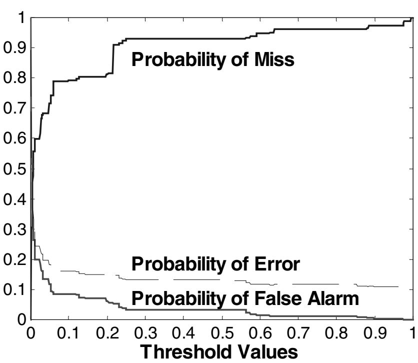


Figure 7: Probabilities of error as a function of the decision threshold

Since there was only one virus attack in our data, we could not meaningfully build an ROC for it. Without the message header or content information, it was impossible to accurately reconstruct the beginning of the attack from the server log. Corporate-wide communications were sent late morning (PST) and defenses were installed across the corporation in the late afternoon of the affected day. The firewall SAC gave a sharp drop in health probability at the 10:51AM interval. As with the long email loops, the SAC evaluators adapted to the presence of the virus and the probability of health did not continue to indicate a problem, despite evidence that the virus was continuing to impact the service.

This is work in progress. An attempt is under way to define evaluators better suited to detecting both the presence as well as the onset of anomalies. We plan to publish those results in a forthcoming technical report.

4. Conclusions and future work

We have presented a general architecture which aims at autonomously assessing the health of service elements in a broad sense, by adding a layer of intelligence on top of the measurement gathering and sending paradigm. That intelligence is provided by a combination of common statistical techniques, packaged in a reusable way, and a probabilistic reasoning technology (Bayesian networks). Our implementation of the architecture is largely domain independent, with a small domain dependent customization layer.

In addition, by utilizing XML to describe the generic notion of probabilistic health and using standard Web protocols (HTTP) to transport it, we enable easy peer-to-peer conversations about component health. This is a broader paradigm than the hierarchical, manager to managed element model.

We have experimented with an instance of this architecture, customized to deal with the email services domain, and targeted at the health anomalies of virus infections and email loops. The experiment, conducted on real-life data from HP firewall mail servers logs, shows encouraging results despite the absence of specificity and sophistication of the sensors, measures and evaluators.

We believe that our proposed architecture is a promising step toward the challenges of managing large and complex services. The approach is general and valid for arbitrary service elements. The absence of a requirement for a detailed and complete model of correct behavior is an attractive aspect of this approach. The prospect of greater sensitivity and accuracy by the combination of statistics and probabilistic reasoning is compelling. The ability to reduce a potentially broad and diverse set of noisy inputs to a single number is another advantage of the approach. The domain dependent components of the architecture and with it, the attendant required customization efforts, are small.

To realize the full potential of these concepts requires more research. As well as additional experiments involving customizations of the SAC architecture to various domains, we intend to extend this work in a number of ways. We are researching the application of more sophisticated statistical and probabilistic reasoning technology, specifically learning, to make the health awareness machine more accurate. We hope to further explore the self-control part of this 'Self-Awareness and Control' architecture. We also intend to explore what happens when we build SACs of SACs.

Acknowledgments

Sincere thanks to Alan Karp of HP Labs for key suggestions during the inception of the SAC idea, and to Marsha Duro of HP Labs for strengthening the evaluation of that idea during the gestation of this paper. We are also grateful to the IM reviewers and shepherd, Gabriel Jakobson, for improving the signal-to-noise ratio of our document.

References

[1] J. Madden, CA begins shipping 'Neugent' neural network agent *eWEEK*, Dec, 1998.

[2] G. Jakobson and M.D. Weissman, Alarm correlation *IEEE Network*, pp. 52-59, Nov, 1993.

[3] G. Jakobson and M.D. Weissman, Real-time telecommunication network management: extending event correlation with temporal constraints eds. A.S. Sethi, Y. Raynaud, and F. Faure-Vincent. pp. 290-301, 1995. Proceedings of the IEEE/IFIP 4th international symposium on integrated network management IM-95 Chapman and Hall.

[4] S. Klinger, S. Yemini, Y. Yemini, D. Oshe, and S. Stolfo, A coding approach to event correlation eds. A.S. Sethi, Y. Raynaud, and F. Faure-Vincent. pp. 266-277, 1995. Proceedings of the IEEE/IFIP 4th international symposium on integrated network management IM-95 Chapman and Hall.

[5] K.R. Sheers, HP OpenView Event Correlation Services *Hewlett-Packard Journal*, pp. 31-42, Oct, 1996.

[6] Service model for email services at Sprint S. Ramanathan, D. Caswell, M. Asawa, and R. Malpani. 1997. HP Labs ISAL. Palo Alto, CA.

[7] Using service models for management of Internet services D. Caswell and S. Ramanathan. HPL-1999-43, Mar, 1999. HP Labs ISAL. Palo Alto, CA.

[8] P. Bhoj, S. Singhal, and S. Chutani, SLA management in federated environments eds. M. Sloman, S. Mazumdar, and E. Lupu. pp. 293-308, 1999. Proceedings of the IEEE/IFIP 6th international symposium on integrated network management IM-99 IEEE Publishing.

[9] J. Pearl. *Probabilistic reasoning in intelligent systems: networks of plausible inference*, San Francisco, CA: Morgan Kaufmann, 1988.

[10] C.S. Hood, Intelligent detection for fault management of communication networks 1996. Rensselaer Polytechnic Institute. UMI Dissertation Services.

[11] C.S. Hood and C. Ji, Proactive network fault detection ed. IEEE. 1997. Proceedings of INFOCOMM 97

[12] C.S. Hood and C. Ji, Intelligent agents for proactive fault detection *IEEE Internet Computing*, vol. 2, pp. 65-72, Mar, 1998-Apr 30, 1998.

[13] D. Heckerman, A. Mamdani, and M.P. Wellman, Real-world applications of Bayesian networks *Communications of the ACM*, vol. 38,Mar, 1995.

[14] C. Skaanning, F.V. Jensen, U. Kjærulff, P. Pelletier, L. Rostrup-Jensen, and L. Parker, Printing system diagnosis - a Bayesian network application pp. 259-265, 1998. Proceedings of the 9th international workshop on principles of diagnosis DX-98

[15] A tutorial on learning with Bayesian networks D. Heckerman. MSR-TR-95-06, 1995. Microsoft Research. Redmond, WA.

[16] HP Internet Business Solutions. Chai. 2000. http://chai.hp.com/

[17] IT-Analysis.com. The future is thin with HP's Chai. 99. http://www.it-analysis.com/99-09-30-2.html

[18] F.G. Cozman, EBayes - Embedded Bayesian networks, rel. 1998. http://www.cs.cmu.edu/~javabayes/EBayes/index.html/

[19] Microsoft DTAS. XML Belief Network File Format. 2000. http://research.microsoft.com/DTAS/bnformat/default.htm

[20] F. Provost, T. Fawcett, and R. Kohavi, The case against accuracy estimation for comparing induction algorithms 1998. Proceedings of the 15th international conference on machine learning ICML-98 Morgan Kaufmann. San Mateo, CA.

Biographies

Alexandre Bronstein works as a Senior Scientist at Hewlett-Packard Laboratories in the Internet and Mobile Systems Lab. He received a BS in mathematics, MS and PhD in computer science, from Stanford University, and an RC (reality check) from 7 years in Silicon Valley start-ups. His current research interests are in the area of health: system health professionally, human health as a hobby.

Joydip Das is a Software Architect at Hewlett-Packard. He has over 10 years of experience in developing and architecting software for numerous successful products. He has worked in areas including broadband test and measurement equipment for ATM networks, and satellite test systems. His current interests are in the areas of large scale Internet computing platforms and federated e-services marketplaces. Joydip holds a Master of Engineering – Information Technology degree from Royal Melbourne Institute of Technology and a Bachelor of Engineering - Electrical, from Monash University, Melbourne, Australia.

Rich Friedrich has held several research and product development positions within Hewlett-Packard during the previous 18 years and is now a Principal Architect in the Internet and Mobile Systems Lab. He is currently leading a team researching next generation, large scale Internet computing utilities that support emerging services. He was the program co-chair for the Sixth IEEE International Workshop on Quality of Service held in May 1998. He has published extensively and is a co-inventor on multiple patents. He attended Northwestern University and Stanford University.

Gary (Igor) Kleyner is a Scientist and Software Engineer at Hewlett-Packard Laboratories. He has over 20 years of experience in academic and industrial research and development in the areas of theory of probability and statistics, mathematical physics and modeling, data mining and reliability analysis, internet and e-commerce automation. He has numerous publications in those fields and holds 3 patents. His current interests are in the areas of large-scale computing platforms reliability and internet data mining and analysis. Gary holds two BS degrees in mathematics and engineering, PhD and MS degrees from Saint-Petersburg Technical University and Northwestern University.

Sharad Singhal is Principal Scientist at Hewlett-Packard Laboratories. He has over 18 years of experience in industrial research in a number of areas including speech and video coding, signal processing, middleware technologies and systems management. He has published extensively in these areas, and holds 4 patents. His current research interests are in the areas of systems management for large-scale systems. Sharad holds PhD and MS degrees from Yale University, New Haven, and BTech from the Indian Institute of Technology Kanpur, India.