Elastic Resource Prediction for Cloud Data Center

Thant Zin Tun[1], Thandar Thein[2]
University of Computer Studies, Yangon
thantzintunster@gmail.com[1], *thandartheinn@gmail.com*[2]

Abstract

Cloud data centers offer utility-oriented IT services to users worldwide. The nature of resource demand of cloud data centers is elastic as the overall workloads are always changing. For handling dynamic workload nature ahead of the needs, elastic resource demand prediction is the key issue in cloud data centers. If the cloud provider does not ensure they have enough resources to meet demand which will lead to under or over provisioning of resources. In this paper, integrated elastic resource prediction system is proposed by combining signature-based prediction and state-based prediction approahces. The workload nature of the cloud data centers are both repeating pattern and non-repeating pattern workload. Signature-based prediction is used to predict the repeating pattern workload and state-based prediction is used to predict the non-repeating pattern workload. Integrated Elastic Resource Prediction (IERP) system is used to predict the mixed workload pattern. Feature selection is conducted first to reduce processing overheads while achieving high prediction accuracy. The proposed predictors are implemented and evaluated with real world workload traces which show that they achieve high resource prediction accuracy with above 95%.

***Keywords**: Cloud Data Center, Integrated Elastic Resource Prediction, Signature-based Prediction, State-based Prediction.*

1. Introduction

Cloud computing is a computing model that allows better management, higher utilization and reduced operating costs for datacenters while providing on demand resource provisioning for different customers. The advent of cloud computing has allowed contemporary business owners to rent and use infrastructure resources or services needed to run their businesses in a pay-as-you-use manner [4]. This usage has been made possible by ubiquitous network connectivity and virtualization. Merits of cloud computing over the conventional data center include appearance of infinite computing resources on demand and elimination of an up-front commitment by cloud users.

Resource needs of cloud users often change with time and runtime application behavior is difficult. The resource-management systems should not have need of previous knowledge about applications, such as application behaviors. Moreover, it should not give overheads in development time and should not be costly. Resource demand prediction is a key feature for efficient resource provisioning of dynamic workload. The resource needs for the cloud provider must be predicted in advance so that the resource management system can adjust resource provisioning according to customers' needs.

The cloud provider must ensure they have enough resources to meet demand. Otherwise the provider will need to pay compensation to those customers whose performance criteria have not

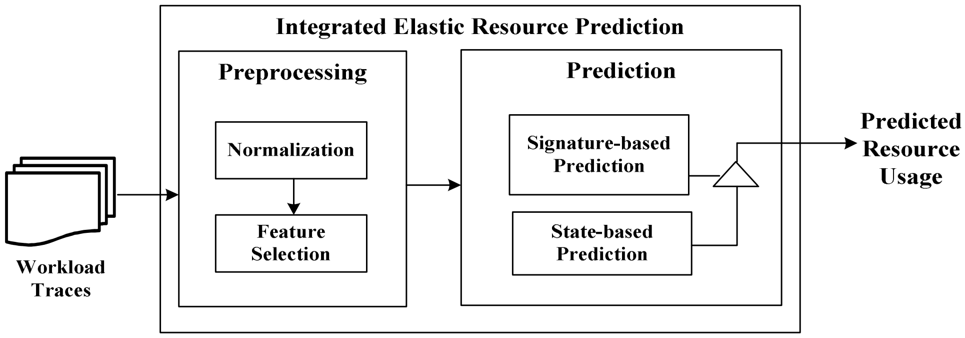

Figure 1. Framework of Integrated Elastic Resource Prediction System

been met, which leads to under provisioning of resources. Then customer dissatisfaction can be occurred. Over provisioning of resources wastes of resources and that could be put to the others.

Signature-based prediction and state-based prediction approaches are proposed to predict the repeating pattern workload and non-repeating pattern workload. Integrated elastic resource prediction (IERP) system is proposed which integrates the signature-based prediction and state-based prediction approaches. The proposed IERP system consists of three main components preprocessing, pattern extraction, and pattern checking and prediction.

In order to reduce processing overheads while achieving high prediction accuracy, feature selection is conducted in preprocessing. First the resource demands are extracted as the patterns. If the repeating patterns are detected, the predictor employs the signature-based approach. Otherwise, it uses the state-based approach for the prediction. IERP is implemented and evaluated with real world workload traces. The framework of IERP is shown in Figure 1.

2. Signature-based Resource Usage Prediction

Signature-based prediction approach is proposed to predict the repeating pattern workload. It calculates the average value of all pattern windows of the repeating pattern signal.

It first calculates the total resource usage of each pattern window as in equation (1). Then calculate the total resource usage of all pattern windows as in equation (2) where *TRS* is total resource usage. The predicted resource usage (*PRU*) is calculated by averaging three consecutive predicted signal values as shown in equation (3).

$$Total(P_1) = \{l_1 + \cdots + l_Z\} \tag{1}$$

$$TRS = Total(P_1) + \cdots + Total(P_Q) \tag{2}$$

$$PRU = \frac{TRS_1 + TRS_2 + TRS_3}{3} \tag{3}$$

3. State-based Resource Usage Prediction

For non-repeating patterns workload, state – based prediction approach is proposed by using Discrete Time Markov Chain (DTMC) where resource usages are considered as a metric x. The example of a state-based resource demand prediction model is shown in Figure 2 where the metric value ranges from 0 to 40, and this ranges are partitioned into four states. It discretizes resource usage values into N equivalent width bins where each bin denotes a different state. In this experiment, N=40 bins is used by analyzing the number of bins based on the prediction accuracy.

The transition probability matrix P_x is built, which is an N×N matrix to build the prediction model of metric x by Markov Chain. The element p_{ij} at row i and column j of P_x represents the conditional probability of making a transition from state i to state j. It can derive the probability distribution for metric x after t time units as shown in equation (4) where π_t and π_0 denote the probability distribution at time t and the initial probability distribution for the metric x, respectively. Given a current state i, the state-based predictor predicts the state at a future time t by extracting the most possible future state j from the matrix P^t_x at row i.

$$\pi_t = \pi_{t-1}P_x = \pi_{t-2}P_x^2 = \cdots = \pi_0 P_x^t \qquad (4)$$

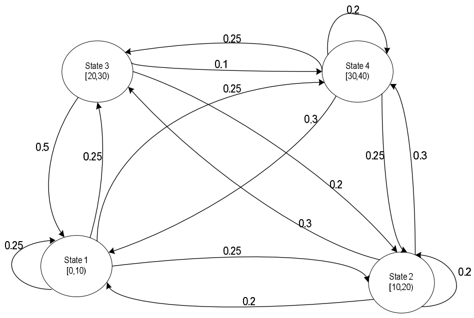

Figure 2. State-based Prediction Model

4. Integrated Elastic Resource Usage Prediction

IERP is used to predict both repeating and non-repeating pattern resource usage. It consists of three phases, preprocessing phase, pattern extraction phase and pattern checking and prediction phase.

In the preprocessing phase, the workload trace is first normalized, and the important features are selected using Principal Components Analysis (PCA). The selected features are used to extract the pattern windows of the resource usage. Signal processing technique is used to extract the patterns of the resource workload. The pattern windows are then checked the repeating pattern or non-repeating pattern of the workload. When it detects the workload as the repeating patterns, they are called as signature and use the signature-based prediction. If the repeating pattern is not discovered, it employs the state-based prediction approach.

4.1. Preprocessing

The process flow of preprocessing phase is shown in Figure 3. The workload traces are normalized first and feature selection is performed.

The workload traces contain many features such as *Job Number, User ID, Group ID, Requested Memory, Requested CPU, Submit Time and Wait Time* and so on. All features of them are not needed for the resource usage prediction. Therefore, feature selection is performed to extract the highly related and important features for the prediction by applying the PCA. PCA is a mathematical procedure that uses orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variable called principal components. PCA studies linear relations among variables. It is performed on the covariance matrix or the correlation matrix. At the first, the correlation matrix is built for all features of the workload. It derives the cross correlation r at delay d by the following equation where mx and my are the means of the corresponding series as shown in equation (5).

$$r = \frac{\sum_i[(x(i) - mx) * (y(i-d) - my)]}{\sqrt{\sum_i(x(i) - mx)^2}\sqrt{\sum_i(y(i-d) - my)^2}} \tag{5}$$

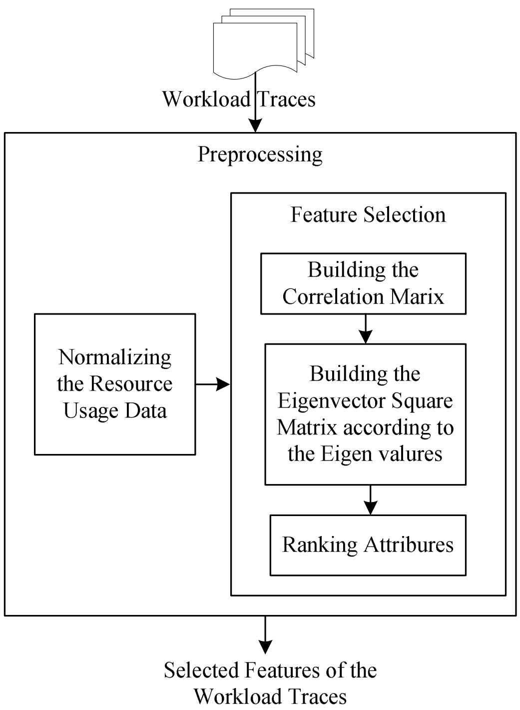

Figure 3. Process Flow of Preprocessing

Then the eigenvector square matrix according to its eigen values is built from the correlation matrix. The attributes are ranked by the eigenvector and eigen values. It is then performed the feature selection with highest ranked features. In this work, three workload traces from Parallel Workload Archives [11] are used. The summary of these datasets is shown in Table 1 and the important selected features by using PCA are described in Table 2.

Table 1. Summary of Experiment Dataset

Dataset	OS	No. of CPUs	No. of Nodes	No. of Jobs
Anon	Linux OS	1024	560	1020195
HPC2N	Linux OS	240	20	202876
CEA-Curie	Changed with time	1440	360	312827

Table 2. Selected Features of Workload Traces

Anon	HPC2N	CEA-Curie
Job ID	Job Number	Job Number
Submit Time	Submit Time	Submit Time
Wait Time	Wait Time	Wait Time
Run Time	Run Time	Run Time
Nprocs	No. of Allocated Processors	No. of Allocated Processors
Used Memory	Average CPU Time Used	Average CPU Time Used
ReqNprocs	Used Memory	Used Memory
ReqTime	-	Request Number of Processors
Status	-	-

4.2. Pattern Extraction

The process flow of pattern extraction phase is illustrated in Figure 4. IERP employs the Fast Fourier Transform (FFT) to convert the resource usage from time domain to frequency domain. FFT is employed to calculate the dominant frequencies of resource workload. The dominant frequency (f_d) is the most occurring frequency of the signal, where selection of the longest repeating patterns that was observed [5].

$$Z = \frac{1}{f_d} \times r \tag{6}$$

$$Q = \frac{W}{Z} \tag{7}$$

$$P_1 = \{l_{1,} \dots, l_Z\}, \dots, P_Q = \{l_{(Q-1)Z+1,} \dots, l_{i.QZ}\} \quad (8)$$

Given a dominating frequency f_d, IERP calculates size of a pattern window (Z) as shown in equation (6) where r is the sampling rate. The original resource workload is $L = (l_1, \dots, l_W)$. Then it is divided into Q pattern windows as equation (7). The pattern windows are shown in equation (8).

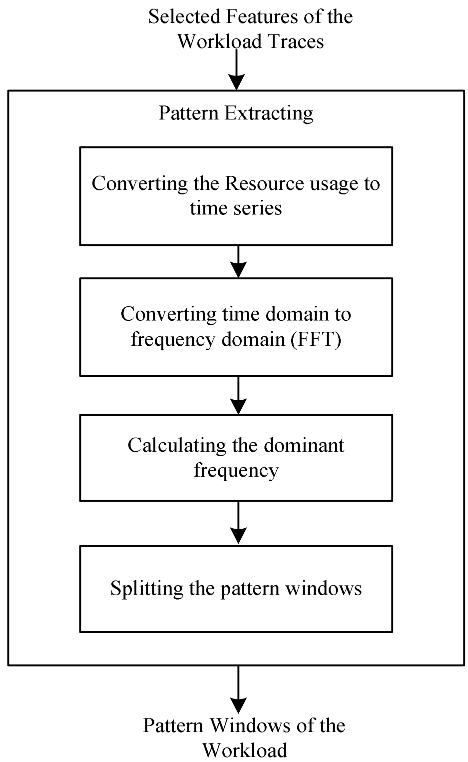

Figure 4. Process Flow of Pattern Extraction

4.3. Pattern Checking and Prediction

To discover whether the pattern windows are repeating or not, IERP calculates the similarity between P_i and P_j which are all pairs of pattern windows by employing Pearson correlation as in equation (9).

$$\rho_{P_i,P_j} = \frac{cov(P_i, P_j)}{\sigma_{P_i}\sigma_{P_j}} \quad (9)$$

If their Pearson correlation is close to 1 (>0.85 in this experiment) the two pattern windows are similar. The process flow of pattern checking and prediction is shown in Figure 5. If all pattern windows are similar, IERP considers the resource workloads are repeating patterns and called signature. Then it uses the signature-based approach for prediction. Otherwise, it considers as the non-repeating patterns and employs the state-based prediction approach.

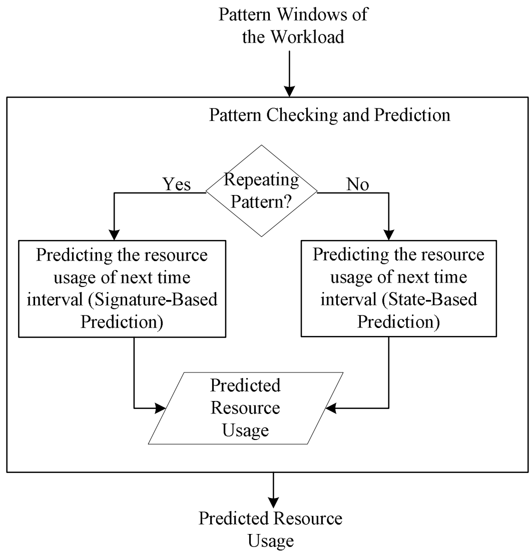

Figure 5. Process Flow of Pattern Checking and Prediction

5. Experimental Set Up

Signature-based prediction, state-based prediction and IERP system are implemented and conducted these experiments on four workload traces: Parallel Workload Archives and Google Cluster Workloads [2, 10]. The prediction intervals (1, 2 and 3 minutes) for four workload traces are set for prediction. The data extracting example from Google Cluster dataset is shown in Figure 6. The average records for 1 minute interval are 8000. Although IERP is able to manage I/O, memory and network usage, the CPU resource usage is focused in the experiment.

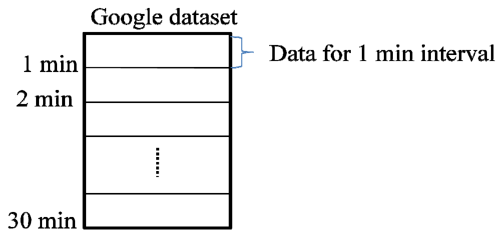

Figure 6. Data Extracting Example of Google Workload

6. Experimental Results

The prediction implementation is tested using four workload traces. The prediction accuracy is calculated as the percentage of the fraction of the predicted workload and actual demand. Signature-based prediction is evaluated with repeating pattern workload and state based prediction is evaluated with non-repeating pattern workload of real world workload traces. Then IERP is evaluated on the real world workload traces, which is the mixed workload pattern with both repeating and non-repeating pattern.

6.1. Evaluation of Signature-based Predictor

The prediction accuracy of Signature-based prediction is shown in Figure 7. Figure 7 shows the prediction accuracy of four workload traces for 1, 2 and 3 minutes intervals. According to this Figure, it can be seen that signature-based prediction scores high accuracy for four workload traces.

It achieves the prediction accuracy of 98%, for 1 minute interval and 97% and 96% are achieved for 2 and 3 minute prediction intervals respectively over the Google Cluster workload. The same prediction accuracy of Anon workload trace is achieved at 97% for 1 and 2 minute intervals and 96% is achieved for 3 minute interval. For the CEA-Curie workload trace, the maximum prediction accuracy is 98% for 1 minute prediction interval and 97% for 2 minutes and 95% for 3 minutes prediction intervals. The prediction accuracy of 97% is achieved for 1 minute interval and 96% and 95% are achieved for 2 and 3 minutes intervals on HPC2N workload.

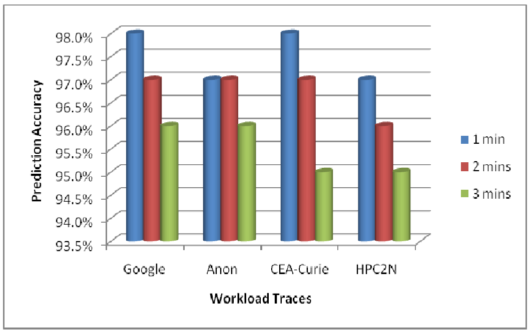

Figure 7. Prediction Accuracy of Signature-based Predictor

6.2. Evaluation of State-based Predictor

The prediction accuracy of Stat-based prediction over four workload traces for 1, 2 and 3 minutes intervals are shown in Figure 8. According to the Figure, it can be seen that signature based prediction scores high accuracy for four workload traces. It achieves the prediction accuracy of 97%, for 1 minute interval and 96% are achieved for 2 and 3 minute prediction intervals respectively over the Google Cluster workload.

The prediction accuracy of Anon workload trace is same as the Google workload in state based predictor. For the CEA-Curie workload trace, the maximum prediction accuracy is 98% for 1 minute prediction interval and 96% for 2 minutes and 95% for 3 minutes prediction intervals. The prediction accuracy of 96% is achieved for 1 minute interval and 95% is achieved for 2 and 3 minutes intervals on HPC2N workload.

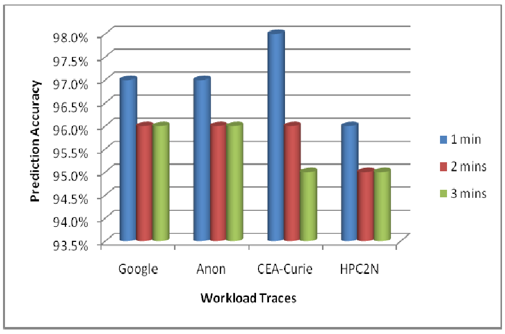

Figure 8. Prediction Accuracy of State-based Predictor

6.3. Evaluation of IERP Predictor

The prediction accuracy of IERP over four workload traces for 1, 2 and 3 minutes intervals is shown in Figure 9. According to Figure 9, it can be seen that IERP scores high prediction accuracy for four workload traces. IERP achieves the prediction accuracy of 98% over the Google Cluster workload for all prediction intervals.

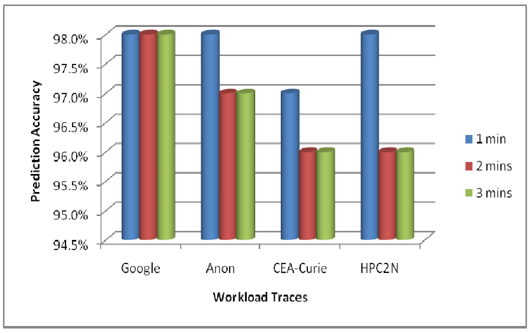

Figure 9. Prediction Accuracy of IERP Predictor

The prediction accuracy of 98% is achieved for 1 minute interval and 97% is achieved for 2 and 3 minutes intervals on Anon workload. For the CEA-Curie workload trace, the maximum prediction accuracy is 97% for 1 minute prediction interval and 96% accuracy for 2 and 3 minutes prediction intervals. The prediction accuracy of 98% is achieved for 1 minute interval and 96% is achieved for 2 and 3 minutes intervals on HPC2N workload.

7. Related Work

Z. Gong et al. [9] proposed the PRESS, a light-weight signal processing and statistical methods to predict dynamic resource demands and perform elastic VM resource scaling based on the prediction results. They implemented and evaluated using RUBiS benchmarks driven by real-life workload traces, and a resource-usage trace of a Google application workload. The prediction accuracy for PRESS are 96% for ClarkNet, 93% for WorldCup and 78% for Hybrid workload traces where there are quite large ranges of the ratios between the predicted load and the demand (the under-estimation errors).

E. Caron et al. [3] proposed an approach to the problem of workload prediction based on identifying similar past occurrences to the current short-term workload history and presented in detail the auto-scaling algorithm. S. K. Garg et al. [6] used an artificial Neural Network based prediction model by using standard Back Propagation (BP) algorithm for prediction. The number of hidden layers is varied to tune the performance of the network and through iterations it was found to be optimum at the value of 5 hidden layers.

A. Khan et al. [1] introduced a method based on Hidden Markov Modeling (HMM) to characterize the temporal correlation in the discovered server clusters and to predict variation in workload patterns. X. Zhou et al. [8] proposed extended Evidential Markov chain and can cope with noisy data stream. This study applies ensemble classification to identify system anomaly based on the predicted metrics.

X. Kong et al. [7] presented a fuzzy prediction method to model the uncertain workload and the vague availability of virtualized server nodes by using the type-I and type-II fuzzy logic systems. They also proposed an efficient dynamic task scheduling algorithm named SALAF for virtualized data centers.

8. Conclusion

In this paper, design and implementation of signature-based predictor, state-based predictor and IERP predictor for cloud datacenters are presented. Resource demand in cloud datacenters often change with time and the runtime application behavior is difficult to predict. The resource management system of cloud data centers should not require prior knowledge about applications. The elastic resource prediction system is proposed by employing light-weight signal processing and statistical learning approaches for the predictors. In order to reduce the processing overheads, the feature selection is conducted to the prediction system by employing PCA. The prediction system is evaluated on real world workload traces. Evaluation results of the prediction approaches show that they achieve high prediction accuracy with above 95%. The proposed predictors are efficient light-weight prediction approaches for the resource provisioning system of cloud data centers.

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