PREDICTION BASED TASK SCHEDULING IN DISTRIBUTED COMPUTING†

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1 INTRODUCTION

The effectiveness of task scheduling in a distributed environment is critically dependent on the timely identification of the least loaded nodes. Whether the issue of interest is load-sharing or distributed parallel computation, overall system performance is determined in large part by the characteristics of the nodes participating in a particular computation. The diversity of node characteristics across the network frequently results in a spectrum of available compute powers on different nodes. Due to the high cost of task migration, effective evaluation of the relative available compute powers of the nodes in the network and the use of that information in task distribution are essential components of successful task scheduling in a distributed environment.

A few implementations of systems for distributing large scale computations over a network of computers rely on schemes based on the current as well as the prior state information on each node to make better task distribution decisions [2]. The goal of such algorithms is to uncover the hidden information that may be present in the past load data, and use that information to better evaluate the available compute power of the nodes in the network. These approaches tend to rely on extensive fine-tuning often due to the ad-hoc design of the data analysis procedures employed.

We present a systematic and statistically sound method for uncovering the information present in the past load data and using that information to predict the future processor load. Using time series statistical methods we analyze the compute intensive load on actual and simulated processors to identify stochastic models that suitably represent the load behavior on those processors. We then use these models to obtain the minimum mean square error load forecasts for various times in the future and discuss how they can be used in task scheduling in distributed systems. In particular, we use

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these forecasts to reduce the performance degradation caused by the outdated state information resulting from delays in collecting it.

The performance of the minimum mean square error load forecasts are then compared against those obtained by using the current load levels as predictors of the future state of the nodes. We show that the relative performance of these approaches depends on factors including the statistical characteristics of the load on each processor and the number of nodes in the system.

2 TIME SERIES ANALYSIS

Conceptually, the load on a processor can be modeled by a theoretical stochastic process. In the following, we express the computation load on a processor by the length of its CPU ready queue. Let $x_t$ denote the load on the processor $X$ at time $t$. We refer to the sequence $\{x_{t-j}\}$, where $j = 1, 2, \ldots$ as the load time series on node $X$. The special feature of this type of load time series is the fact that successive observations are usually not independent and that any analysis of such time series must take into account the time order of the observations. Since successive observations are dependent, future values may be predicted from past observations. The load time series are stochastic in that the future is only partly determined by past values, so that exact predictions are impossible and must be replaced by the idea that future values have a probability distribution which is conditioned by a knowledge of past values. The information present in the load time series can be extracted by appropriate statistical analysis methods.

2.1 Preliminaries

Suppose $\{a_t\}$ is a sequence of independent and identically distributed random variables from a distribution with mean zero and variance $\sigma^2$. A powerful model for describing time series is the general autoregressive integrated moving average (ARIMA) process of order $(p, d, q)$, defined by

\[
\Phi(B)w_t = \Theta(B)a_t
\]

where

\[
w_t = \nabla^d x_t = (1 - B)^d x_t,
\]

\[
\Phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p,
\]

\[
\Theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q,
\]

and where $B$ is defined by $Bz_t = z_{t-1}$ for any time series $\{z_t\}$. The operators $B$ and $\nabla$ are called the backward shift and the backward difference operator respectively. The coefficients $\phi_i$ and $\theta_i$ are constants.

Given a model ARIMA$(p, d, q)$ and a time series $\{x_{t-j}\}$, where $j = 1, 2, \ldots$ generated by it we would like to forecast the value of $x_{t+l}$, where $l \geq 1$, when we are currently