A parallel workload has extreme variability in a production environment

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ABSTRACT

Writing data in parallel is a common operation in some computing environments and a good proxy for a number of other parallel processing patterns. The duration of time taken to write data in large-scale compute environments can vary considerably. This variation comes from a number of sources, both systematic and transient. The result is a highly complex behavior that is difficult to characterize. This paper further develops the model for parallel task variability proposed in the paper “A parallel workload has extreme variability” (Henwood et. al 2016). This model is the Generalized Extreme Value (GEV) distribution. This paper further develops the systematic analysis that leads to the GEV model with the addition of a traffic congestion term. Observations of a parallel workload are presented from a High Performance Computing environment under typical production conditions, which include traffic congestion. An analysis of the workload is performed and shows the variability tends towards GEV as the order of parallelism is increased. The results are presented in the context of Amdahl’s law and the predictive properties of a GEV models are discussed. A optimization for certain machine designs is also suggested.

1. INTRODUCTION

Performance models of high performance computer (HPC) systems enable architects and administrators to gain insight into optimal system configuration for their applications. Models also provide valuable comparison against measured values that can be used to evaluate the behavior of system components (for example network, storage nodes). A common approach is to directly observe a mean value for the property of interest (bandwidth or latency for example) and with domain expertise, historical knowledge, and instantaneous system insight, judge if the measured value is tolerable.

In the paper “A parallel workload has extreme variability” [6] it is claimed that the duration of time taken for a sufficiently parallel workload to complete should follow the Generalized Extreme Value (GEV) distribution shown in Eqn 1. A parallel write makes a good choice for study as it is common, well understood, and a good proxy for other common parallel operations, including map-reduce, and sharded databases.

\[
P_{\mu,\sigma,\xi}(x) = \begin{cases} 
\exp \left( - \left( 1 + \frac{\xi(x-\mu)}{\sigma} \right)^{-1/\xi} \right) & \text{if } \xi \neq 0 \\
\exp \left( -e^{(x-\mu)/\sigma} \right) & \text{if } \xi = 0
\end{cases}
\]  

(1)

Extreme value theory and significant observations of the GEV across many scientific disciplines. The modern theory can be traced back to Fisher and Tippett in the 1920s [3]. A brief description of their discovery and recent important observations of extreme phenomena are recorded in [6] and references therein.

The argument presented for GEV in parallel environments is, in essence, that the parallel task is executed by workers that are completely independent with identical distribution (IID). The duration of the parallel task \(T_g\) is measured when the worker \(S_n\) is complete:

\[
T_g = \max\{S_1, S_2...S_m\}.
\]  

(2)

These criteria broadly meet the preconditions for extreme value theory to be applicable. And hence \(T_g\) is approxi-
mated by $P(x)$ in Eqn. 1. The authors then present results for a carefully constructed setup that attempts to minimize external perturbations and focuses on solely on the period when the workload is running under IID conditions.

This paper builds on work by studying a parallel workload in a production HPC environment. The chosen workload is more typical to an actual workload and the duration studied includes some serialized setup time. The environment is a multi-user environment and no precautions have been taken to limit any other simultaneous activity on the system. This paper argues that the extreme distribution should follow a Fisher-Tippett Type I (“Gumbel”) distribution. A framework for data analysis of extreme statistics [1] is applied to distinguish between the different Fisher-Tippett asymptotes.

2. EXPERIMENT

In changing from the controlled environment constructed in [6] to a multi-user production HPC environment in this study, two notable differences must be understood. Namely: traffic from external activates and network topology.

2.1 Traffic from external activities

$T_\xi$ in Eqn[2] is defined in [6] as the quiescent performance of the file system under study. Let us simply assume that the observed duration of a task on a system with congestion (from other jobs accessing the shared resource) is the quiescent duration $T_\xi$ with a delay of $T_q$ due to external congestion. i.e.

$$T_p = T_s + T_q.$$  \hspace{1cm} (3)

- $T_s$ is the observed write time of a fixed size transfer.
- $T_q$ is the quiescent write time of a fixed size transfer.
- $T_p$ is the time required to resolve resource contention on a multi-user system.

By formalizing the affect of external congestion we now make the following claim: provided the congestion factor ($T_c$) is constant throughout the period of experimental observation, it can be ignored for the purposes of identifying the distribution present.

2.2 Network topology

From the perspective of the task in question, the worker nodes (storage nodes in this case) are all assumed to be the same distance away. Depending on the configuration of the HPC cluster, this may, or may not be the case. In this study, we chosen a HPC cluster (Ranger) is chosen where this requirement typically holds.

The experiment has two parts. The first part is designed to measure the distribution of a typical write. The second part of the experiment applies the framework described by Chapman, Rowlands, and Watkins [1] to verify the presence of a member of the GEV family with $\xi = 0$ in Eqn. 1. With $\xi = 0$, the GEV distribution would specialize to the Gumbel distribution [4, 2].

2.3 Environment

Experimental data were collected during the summer of 2012 on the Ranger HPC environment [7] operated by the Texas Advanced Computer Center at The University of Texas at Austin. Ranger is a Sun Constellation Linux cluster with system components connected via a full-CLOS InfiniBand interconnect. Eighty-two compute racks house the quad-socket compute infrastructure. A high-speed parallel Lustre file systems is provided running across 72 I/O servers.

The experimental runs were executed as normal user jobs during a normal production operation. The parallel file system is a Lustre file system (v 1.8.5) on Red Hat* Enterprise Linux* 5, the client nodes are Red Hat* Enterprise Linux* 5.

2.4 Workload definition

For the purposes of both identifying the underlying variability and testing for particular member of the GEV family a typical write is defined as:

- Total file size is 16GB (half the available client memory.)
- 16 storage nodes are used, a single 1GB stripe is written to each storage node.

A 1GB stripe size is chosen to ensure the effect of a serialized metadata request (a restriction imposed by the Lustre 1.8 file system) is small and the write time from the perspective of the client is dominated by variability in the storage nodes. 16 nodes are chosen as a level of parallelism sufficient to exhibit GEV behavior.

The tool dd (v 5.2.1) is used to complete the write. A block size of 16GB is specified. A single directory is used for all writes. /dev/zero is used as the data for the write and is chosen to ensure the client node does not stall waiting for data to write. During this phase, the write is repeated 100 times to ensure sufficient fidelity of the resulting distribution.

```
$LUSTRE = '/scratch/writetest' # directory
# on the parallel file system
$SSZ = 1024 # each stripe is 1GB stripes
$SCT = 16 # number of stripes to write is 16
$FILESIZE = $SSZ * $SCT
lfs setstripe -c $SCT -s ${SSZ}M $LUSTRE

$FILESIZE = $SSZ * $SCT
# on the parallel file system

$lustre = '/scratch/writetest'
# directory
$SCT = 16
$FILESIZE = $SSZ * $SCT
lfs setstripe -c $SCT -s ${SSZ}M $LUSTRE
for i in {0..100} do; \
  sleep 30
  time dd if=/dev/zero of=$LUSTRE/${i}.dat \n    bs=${FILESIZE}M count=1 \n    >>~/results.txt; \
  done
```

To ensure 16 storage nodes are written in parallel, a Lustre control code (lfs setstripe) is used to define the striping on the destination folder. The client node enters sleep for 30 seconds between writes to mimic a computation load that may be present during a typical application. Once the write is complete, time diagnostics are written including the absolute elapsed real time, which is the measure of interest $T_p$. Diagnostics are written from the client to a separate file system. Note: the dd tool on the Ranger environment is unable to write a block size of larger than 2GB. If a blocksize is specified larger than this limit, 2GB is written and the task ends.

2.5 Testing for a specific member of the GEV family

Chapman, Rowlands, and Watkins [4] provide a method for identifying the presence of values distributed with the
Gumbel distribution (where $\xi = 0$ in Eqn. 1) by exploiting the fact the value of the third central moment (skewness) of the Gumbel distribution is constant ($\approx 1.14$). The tools and setup are identical to the previous experimental phase. Instead of fixing on 16 storage nodes, the method requires a sweep of increasing storage node counts.

The method is as follows: One hundred 1GB writes are completed against a single storage node and the skewness calculated from the distribution of the elapsed time measurements. The experiment is repeated, this time writing one GB each to two storage nodes. Storage nodes and GBs are added until a limit is reached and for each addition 100 writes are performed and the skewness is calculated for the 100 experimental runs. In practice, $SSCT$ is incremented in the code example above.

As the number of storage nodes increases, the measured skewness of the data should converge on the Gumbel skewness value. Chapman, Rowlands, and Watkins [1] point out that the speed of the convergence is dependent on the underlying distribution from which the maximum (or minimum) is selected.

3. RESULTS

Fig[1] shows the distribution of 100 typical writes designed to deliver a load characteristic of large file count per directory large I/O’s checkpoint. The plot (a) focuses attention to the state of the fit around the distribution’s head. The quantile plot (b) emphasises the tail of the fit. Points lying on the line indicate perfect agreement between observation and model. Both the probability plot (a) and the quantile plot (b) show good agreement with the model. The return level plot (c) also indicates good agreement with the model as the points appear within the $95\%$ confidence interval of the value of $\xi$. (d) provides further evidence showing the fitted GEV density function is in good agreement with the data histogram. All figures was generated using the R language [8] using the ismev library [5].

Fig[2] skewness and mean of write times of the individual distributions obtained as the number of storage nodes is increased. A large spread of distributions is present as storage nodes increase from one to 12. Between 12 and 27 the data skewness is near the value for the Gumbel distribution ($1.14$). Beyond 27 storage nodes, the skewness of the data appears to spread away from the Gumbel skewness.

The maximum number of storage nodes included within this experiment was limited to 29. Beyond this count, the client node exhausted local memory and did not successfully complete the write.

4. DISCUSSION

The results obtained from the Ranger system are encouraging. They were obtained with a simple experiment, on a production system running many simultaneous jobs.

Fig[1] shows general agreement with the GEV model. The value of the shape parameter $\xi = -0.01 \pm 0.07$ is close to the shape value for the Gumbel distribution ($\xi = 0$). Observations within the tail may appear to diverge slightly from the model, but remain well within the margin of error ($95\%$).

If we consider Amhald’s Law:

$$S_{\text{latency}}(s) = \frac{1}{(1 - p) + \frac{\xi}{s}}$$  \hspace{1cm} (4)
This equation gives the theoretical speedup in latency of a parallel task given the proportion of the task that executes in parallel. In the previous study of GEV in parallel environments, the proportion of the application that executed in parallel was made as close to 100% ($p = 1$) as possible. With the use of $dd$ to dispatch the parallel workload in study, there is a non-zero period of the task spent performing the serial metadata operations before the parallel work begins. This suggests that GEV variability is also present for workloads where $p \approx 1$.

Fig. 2 indicates a rapid convergence towards the Gumbel distribution from one to 12 storage nodes. Between 12 and 27 storage nodes, the skewness of the distribution is close to the Gumbel skewness. Beyond that value, the skewness is less like Gumbel.

One possible explanation for the trend away from Gumbel skewness with higher storage node counts is congestion from external traffic. As the storage node count increases on a multi-user system, it is much less likely the assumption to reduce $T_\theta \to 0$ in Eqn. 4 will hold. i.e., while there are a large number of storage nodes available, as the client writes to an increasing number, the probability another job will also be requesting the same storage node resources increases. If a storage node is under higher load it may service requests with a distribution that is not identical to an unloaded storage node.

Fig. 3 presents the cumulative distribution of the GEV model. The model uses the parameters extracted from the fit in Fig. 1. A graphical technique for classifying the likelihood that a particular write will take a given duration is shown with dotted lines. In this case, the example write is observed to take 26 seconds. A vertical line is drawn from the measure of 26 on the abscissa to intersect the cumulative distribution function. From this point of intersection, horizontal line is drawn to the ordinate intersecting at a probability of about 98%.

The result in the example presented in Fig. 3 is that the probability a write will take 26 seconds or less is about 98%. In contrast, writes that take more than 26 seconds have a probability of about 2% - or occur approximately once for every 50 writes. Given this, if a client observes more than one write in 50 taking longer than 26 seconds an alert could be issued.

5. CONCLUSIONS

Understanding and predicting the behavior of high performance computers is a challenging task. Even after they are constructed and operating the measurement, benchmarking, and monitoring of large computers is still an art, practiced by a small number of experts. This paper presents extreme value theory as a new tool to enhance diagnostics. Taking the required measurements to reveal the I/O distribution for a given machine is shown here to be simple and quick to complete. Performing such measurements on a quiet system (where $T_\theta = 0$) enables the baseline variation of the environment to be captured. The model presented in this paper can be calibrated for a given environment and periodic observations can reassure a systems operator that the machine is performing optimally. Furthermore, depending on the operations policy of the environment an accurate model for variability may be valuable in pricing service level agreements.

It is interesting to consider a practical outcome of the GEV result for increasing parallel-ism in data transfers: the case where the throughput of the client interface is the narrowest (or equally narrow) bottle neck in the system. In this case, a parallel transfer is constricted at the point of the client. Adding parallelism will have the effect of reducing performance, and increasing variability. Hence, one might conclude that, if possible, a single storage target should be specified for all data transfers.

As high performance computing continues to develop, new libraries become available to simplify interfacing with data objects. For example, the t3pio library provides automatic configuration for MPI applications that use HDF5. Such a library could introduce auto-tuning behavior to avoid congestion from competing file system tasks if the assumption that a write time will have a GEV distribution. A single client node could be calibrated for ideal parallel behavior and measure deviations from this behavior as values that are unlikely according to the GEV model. A more sophisticated client could choose to modify file layout or cross-reference with other anomalous results to identify congestion areas within the system.

Predicting the behavior of a large machine while it is still in design is valuable if accurate. The GEV model for I/O enables a designer to sweep away the complexity of modeling the file system as a series of components. By simulating the parallel file system as a simple GEV (or Gumbel) source it may be possible to arrive at an accurate file system performance metric. It is conceivable that by starting with the specified performance of a single disk and successively applying the GEV model one can now arrive at the probable behavior of the whole storage system.
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