Predicting the workload of a computer system*

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INTRODUCTION

It is a commonly observed phenomenon that the workload on a computer system has a tendency to increase, resulting in poorer service or the acquisition of new, more powerful computers. Since the procurement of a large scale computer is a very lengthy process, it becomes crucial to predict the workload a system is likely to have several years into the future.

Most of today's general purpose third generation computers are used in a multiuser, multiapplication environment. The workload handled by a computer is a composite of the computing needs of all of the users: each putting different resource demands on the systems. Frequently, the load increases as new applications are put on the system, or as users find new ways of making use of the facilities of the system. A commonly used practice is to describe the composite workload in terms of measures such as total CPU hours used, the number of terminal connect hours, or the number of transactions handled. While such measures give an idea as to the load a system handles, they are rarely adequate for prediction purposes.

The major, if not the only, purpose of a computer installation is to meet the computing needs of its user population. A computer system is used for different applications, the nature, volume, and characteristics of which change with time. It is these changes that result in a change in the workload on a computer system. But as the changes in different applications may be different, such changes may not be visible from the composite measures. Therefore, the workload prediction techniques have to take into account each of the components of the workload. In this paper we discuss some techniques which are applicable to the workload prediction problem.

Before we can consider the techniques for predicting the workload of a computer, we need techniques for characterizing the current workload of a system. In the second section we review a workload characterization technique which uses clustering to uncover the natural groupings in the workload. In the third section we discuss the applicability of some of the statistical forecasting techniques to the workload prediction problem. In the fourth section, we discuss the ways in which the cluster description of the system's workload may change and the ways in which such a description may be used to predict future workloads on the system. The fifth section of this paper presents an example of a workload prediction study that was carried out using the techniques discussed in the fourth section. The system described in the fifth section is currently being used for both program development and production work.

THE CLUSTERING APPROACH TO WORKLOAD MODELLING

If a computer system were to be used to carry out a small number of tasks repeatedly, then it would be a rather straightforward task to create an accurate, validated model of the workload. But, for a general purpose computer system that is shared by a large user population creating an accurate workload model is not easy.

In a multiuser environment each user makes a sequence of computational requests to the system. While the request patterns of one user are likely to be independent of the other users present on the system, the time instants at which the requests are made may depend on the system response characteristics, which in turn, depend upon the actions of all of the other users. No reliable models to date have been formulated for the behavior of a user. One often has to infer the behavior of the user based upon the data collected by the system on logs. In its raw form, this information tends to be so voluminous that it can hardly be used directly as a workload model. Therefore, a simplified model has to be created. The problem of formulating accurate workload models then reduces to the problem of finding natural patterns or structures in the huge amount of data available from a system log.

The problem of finding structures in large volumes of data has often been addressed in the field of pattern recognition. As was noted in Reference 4, however, there are some very basic differences between the pattern recognition problem and the workload characterization problem. Primarily, the pattern recognition problem assumes the existence of well defined classes, or groupings, in the observed data. The groupings we are attempting to find in the work-

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load are strictly for the purposes of modelling the workload and no a priori groupings can be inferred. Several of the pattern analysis techniques can, however, be used for workload modelling. In particular clustering has been used successfully for creating workload models.\textsuperscript{4} - \textsuperscript{9}

In using clustering to model the workload, first we select the degree of aggregation by defining the lowest level of detail that we plan to model as a "workstep." Next we describe a workstep as a point in an appropriately defined multi-dimensional space whose axes represent resource usage levels, or other features of a workstep. Next, a set of worksteps is observed on the system and clustered to uncover their natural groupings.

While the validity of cluster based workload models has been well established in several studies cited above, the groupings are shown to change by changing the feature set.\textsuperscript{5, 6} This is quite natural because no a priori groupings exist and thus changing the feature set changes the perspective of the problem. This gives the analyst some flexibility in producing good models by choosing appropriate feature sets.

As noted in the first section, a problem with workload prediction arises from the fact that different groups of applications are likely to change in different ways. By using a cluster based workload model we take into account the characteristics of such individual groups. Before discussing how we can use such models in prediction let us discuss some of the statistical forecasting techniques in terms of their relationship to the workload prediction problem.

**TYPES OF CHANGES OF THE WORKLOAD**

Frequently the statistical forecasting techniques\textsuperscript{10} reported in the literature address themselves to the forecasting of a single variable. The workload of a computer system can hardly be considered univariate. However, for the purposes of discussion we are going to assume that a single unit of work can be defined and that we can talk about such things as the load on a system doubling, or varying in some way, and that we can plot the workload vs time on a graph.

The statistical forecasting literature discusses four basic types of changes that may occur and methods by which they may be predicted. Let us now examine these four types of changes and discuss them in terms of the workload prediction problem.

First, there may be a random stochastic variation in the amount of work performed over a period of time. Second, the amount of work may be a monotonically increasing or decreasing function of time. Third, the amount of work performed may show an oscillatory nature, that is there may be some type of periodic behavior. Finally, there may be abrupt discontinuities in the workload. Of course combinations of these may also occur. Let us consider each of these changes briefly.

**Random variations**

As we noted above, on a system which supports a large user community the workload observed on the system is the composite of the workload generated by individual users. As the independent users may not follow any particular patterns in submitting their processing requests, a sequence of requests from a user may be treated as a stochastic point process.\textsuperscript{11} The system workload may, therefore, be obtained as a superposition of the individual point processes and may be modelled as a random point process. The exact nature of the point process depends on the size of the user population as well as the characteristics of the individual users.

In addition to the point process type of characteristics of the workload, the amount of work to be performed in response to each request may also show a random variation. If we take, for instance, the case where the machine is used primarily for program development, we would typically expect to be able to describe the load supplied by an individual by a pair of random variables drawn from two, possibly different, distributions. First, there is the random factor determining how often the user submits a job. This will depend upon, among other things, how long it takes him to fix any bug found in his previous run. There will also be a random factor in the amount of work that the next job will perform, which will depend upon the program being developed and the type of bug that next appears. Therefore, some random variations in the load on the system may be quite reasonable.

Due to the randomness of such variations they can only be characterized by describing their probabilistic properties. Very little can be done with respect to forecasting them except to forecast the parameters of their probabilistic descriptions. The distributions of the loads may be useful in determining peak loading conditions.

**Monotonic changes**

By a monotonic change in the workload we mean that the amount of work performed by the computer system shows a steady change over time. This change may be observed as a trend and may reflect an increasing or a decreasing workload. In practice, however, the workloads of computer systems have a tendency to increase rather than decrease. The trend shown by such changes may follow any pattern e.g., straight line, quadratic, exponential.

There are several physical justifications for the fact that loads on computer systems tend to increase with time. First many programs that have been in use for a long period of time tend to grow larger and slower as changes are made or new features are added. Second, many programs that have running times proportional to the number of records processed tend to grow longer because each subsequent run is required to process a larger number of records. Third, many installations that perform program development or program maintenance seem to enlarge their staffs and thus present a larger processing load to the central computer system.

As the monotonic changes are likely to follow well defined trend lines they lend themselves well to forecasting. Under the assumption that the trends do not change, a prediction of the workload can easily be made by following the trends.
Oscillatory loads

The workload on a system may show a periodic behavior, increasing and decreasing in an oscillatory manner. We may argue that this is the most frequently observed behavior of computer system workloads. While a computer system may run 24 hours a day, the loads go up and down depending on the hour of the day. This variation may be connected with the user work hours and work habits. Similar types of oscillatory behavior with different periods may have a number of causes. Many installations have tasks which are performed daily, weekly, biweekly, monthly, quarterly, or yearly.

Another example of this phenomenon can be observed at a typical university computer center where the period of the oscillation is one semester. At the beginning of the semester, the load is comprised of the research users running relatively large jobs. As the semester continues the load gradually changes until by the end of the semester the load is comprised of a large number of students running small jobs. Also, as more projects are due at the end of a semester the load increases significantly at that time.

As the system workload is a composite, it may contain components with different periodic behaviors. For predicting the workload at some future time we need to identify each oscillatory component and its period. Spectral decomposition techniques may be used for this purpose.

Discontinuities

When one plots a graph of the amount of work submitted versus time one may find points of discontinuity in the curve or its derivative. These discontinuities correspond to sudden changes in the load on the system. Such abrupt changes may occur for any one of several reasons.

A frequently observed cause of sudden changes in the load on a computer system are changes in its normal operating procedures. Examples of such changes in operating procedures would include switching major files from tape to disk, or switching major applications from batch to time sharing. Both of these changes are likely to introduce rather large changes in the system’s load. In an environment in which separate systems are used for development and production, the changes in the production machine’s load will tend to be very abrupt as applications make the transition from the test phase to the production phase.

If a new application is decided upon and a significant number of new programmers are hired to perform the implementation, then one would expect to see the derivative of the graph of load change abruptly and expect to see the load increase rather quickly there after.

Note that abrupt changes causing the discontinuities are a result of external factors and, therefore, cannot be predicted on the basis of information available from within a system. For the models created on the basis of system measurements such changes have to be treated as random phenomenon. Since these changes may affect the loads drastically they have to be taken into account in any workload prediction. However, since these abrupt changes are due to external factors it may be possible to predict them by examining the external factors. The quantitative impact of these abrupt changes may be less precisely known due to the fact that they will occur in the future and thus cannot be measured.

Composite changes in the load

In the discussion above we observed that all four types of changes are likely to occur in a computer system workload. Examining the causes of such changes we note that they are not mutually exclusive and that the workload changes observed on real systems can only be explained in terms of two or more of these. For workload prediction we have to identify these component change behaviors first.

As the system workload may consist of several segments it is not necessary that all segments of the workload will exhibit similar changes in behavior. In fact, we expect that the change in the behavior of individual components of the workload will be much simpler than changes in the behavior of the overall workload. A way of identifying the segments of the workloads is to use the cluster based characterization.

THE CLUSTER DESCRIPTION OF THE WORKLOAD

In this section we consider the ways in which the cluster description of a computer’s workload may possibly change with time and how the different types of changes in the workload will be reflected in its cluster description.

Predicting changes in the cluster description

If one is using the clustering approach to describe the system workload, the problem of predicting a future workload on the system corresponds to the problem of finding the cluster description for what the workload will be at some point in the future. As stated earlier, the purpose of clustering the workstep population is to obtain a homogeneous group of worksteps that behave in the same manner. Since the total system workload would be composed of the sum of the work supplied by each cluster one would expect to find the future system workload to be composed of the sum of the work supplied by each cluster after the appropriate modifications have been made to the cluster. Therefore, to find the predicted load on the system we must examine each of the clusters that are present in the system workload and determine how each of these clusters will change. We then make the appropriate modifications to the cluster descriptions and from these descriptions find the description for the entire system load. This operation is likely to be easier and more accurate than trying to deal with the entire workstep population at one time. These operations do of course require a rather detailed knowledge of the membership of each cluster as well as knowledge of how these worksteps have been varying in the past and the types of variation that
these worksteps are likely to exhibit in the future. Basically, all cluster analysis allows us to do is to model small segments of the load independently and gives us ways of combining these models into a model of the total system workload. The prediction of these changes may be accomplished using some of the techniques described earlier.

Changes in the cluster description of the load

A cluster taken as an abstract entity only has a limited number of properties that may vary. A cluster can be thought of as having a location in an appropriate n-dimensional space and can move or drift in this space. A cluster has members, that is, it is composed of some worksteps from the total workload population and therefore some things can be said about the distribution of points in the cluster. Finally, a cluster can be used to describe some segment of the total system workload. In addition to the information available about the cluster itself we can analyze the members of the cluster and determine any additional information that we need to know such as their arrival rates or what types of work they performed.

The cluster description of the total system workload is composed of a group of clusters obtained from clustering the workstep population. In addition to the description of the individual clusters as described above we also know the proportion of the total system load attributable to each cluster.

Before discussing the ways in which the cluster description of the workload may change, let us consider what it means for a given cluster to appear in two different cluster runs. If the system is running in a production environment in which the same programs are run repeatedly then two clusters obtained by the analysis of data from two different times are considered to represent the same cluster if the cluster obtained from the second run contains most of the members of the cluster obtained from the first run. In a nonproduction environment, where different programs are run each day, this method of identifying clusters cannot be applied. Here we have to ascertain what type of job constitutes the cluster in question and to find the similar type of cluster in the output of the later cluster run. For example, in a university workload one would expect the amount of resources used by small student programs to grow with time. Therefore, if one found a cluster both from the beginning of the semester and a cluster from the end of the semester which contained most of the jobs from the introductory programming class then one would say the two clusters correspond even though no single job appears in both clusters.

Since a cluster has a position or location in an n-dimensional space its location may change with time. This would occur if most of the worksteps which made up the cluster changed their feature values in approximately the same way. If this were the case, and some of the worksteps did not change in the same manner as the rest of the worksteps then those worksteps would move with respect to the cluster mean. They may in fact move far enough away from the cluster mean so as to be eliminated from the cluster entirely. When the mean of a cluster moves it is quite likely that some points not previously in the cluster would become close enough to the cluster mean to be absorbed into the cluster. Thus, when a cluster drifts it is not unusual to find that some old members leave the cluster and some new members are added to the cluster. This type of change in the cluster description would of course correspond to the case where there was some monotonic change in the amount of system load, that is whether some or all of the worksteps originally contained in this cluster increased in size.

If a cluster contains worksteps which change in different ways over a period of time, the cluster may fall apart. If this happens the worksteps which were in this cluster may drift close enough to other clusters and join them. As a result the percentage of the total system workload attributable to each cluster may change also.

Another type of change in the workload that may change the cluster description of the workload is the introduction of new applications to the system, or changes in the operating mode of existing applications. In many cases the easiest way to handle such predicted changes is to treat the new or changed application as if it were a cluster by itself. This may be necessary since one might have to estimate the resource requirements of the new application as no measured data may be available. Therefore, one might want to handle this cluster in a different manner than the clusters that were obtained by observing the load on the system.

The applications that already exist but are having their operating mode changed, such as being changed from batch to timesharing or from tape to disk, could be treated the same as entirely new applications except that somewhat better estimates may be made for their resource requirements. These worksteps can be handled by removing them from the cluster to which they belonged and treating them as if they were a separate cluster by themselves.

An oscillatory change in the amount of work performed by the system, or a random variation in the amount of work performed by the system, would typically not involve a real change in the description of the clusters themselves, but rather would involve a change in the number of points assigned to each cluster. Therefore, the variation in the load would be primarily attributable to changes in the arrival rates for the worksteps belonging to the various clusters.

It should be noted that the above techniques need only be applied if a substantial portion of the load is expected to change. If only a few small worksteps are expected to change then the effect on the total system load may be extremely small and can be isolated to one or two clusters.

Predicting changes in applications

An application which continues to be processed over a period of time is often used to process transactions or records of some type. While the computer resources that will be required may not be easily predicted, in many cases an accurate prediction can be made of the number of transactions, or the number or records that will be processed as
these numbers are tied to external factors that may be precisely known or easily predicted. For example, the rate of increase of a payroll processing program depends on the rate of increase in the size of the employee records file, which in turn depends on the rate at which the employment in the company is going to change. Changes in employment levels are usually controlled by the management and can be used to project the resource requirements of the payroll program.

In cases such as this, a far more accurate prediction of the future systems load may be made by first forecasting the changes that will occur at the applications level and then mapping these changes into changes at the resource usage level. In some cases this method will be the only way in which reasonable estimates may be made of the future systems workload.

When an abrupt change occurs in the load the changes are almost always attributable to external factors such as changes in budget levels, the introduction of new applications, or other factors that are clearly known in advance. In these cases the changes in the computer load must also be predicted at the applications level and then the expected computer load must be determined based on these predictions.

Clearly the accuracy of the predictions of the applications workload will depend on the accuracy with which the influences of the external factors can be determined.

AN EXAMPLE

In this section we present an example of how the techniques described in the preceding section can be used to predict the load on a real system. One of the difficulties in describing the results of a prediction study is that the accuracy of the prediction may not be determined for several years. Therefore, the importance of this example is not that it purports to be a complete prediction of the load on a given system, which it is not, but rather that it serves to illustrate the techniques involved than if we had attempted to give a detailed description of all of the data.

The data used in this example was drawn from work done predicting the load for an installation that operates two IBM 370/158 computers. These machines, which are used for program development and the execution of several production systems, process approximately 20,000 job steps per month. This workload prediction study was performed because a need for a replacement for the two 370/158’s had been identified and it was necessary to produce a benchmark to aid in the procurement of this replacement system. The new system was to be sized such that it would satisfy the needs of the installation for a five to eight year period. Therefore, a benchmark had to be produced to represent the load five years in the future.

This installation was chosen as the example for this paper because the load shows many of the types of variations discussed above. First, the basic data set that is used by some of the production systems will be moved from tape to disk in the near future. In addition, one of the production systems will soon have its operating mode changed from batch to timesharing. The program development portion of the workload can be expected to increase due to the modifications and enhancements being made to the production systems.

Seven features were extracted for each of the job steps and the job steps were clustered using the techniques in References 4-6. This clustering produced twenty clusters, ranging from a cluster of thirty executions of the same workstep to a cluster of over 10,000 relatively small worksteps. Rather than presenting data on the twenty clusters and over 20,000 data points in a seven dimensional space, the discussion below will deal with only a few of the clusters and some representative data points. In addition, the data presented in the example is presented in terms of only two features rather than the original seven features. We feel that by presenting the data in this manner we will be better able to illustrate the techniques involved than if we had attempted to give a detailed description of all of the data.

The scatter plot of Figure 1a represents a cluster of worksteps from two distinct classes of production systems. For the purposes of this discussion only two features, tape EXCP’s and disk EXCP’s are shown. The worksteps in the two classes perform essentially the same task, that is editing input data and processing updates to a large master file. There is no way, based upon their resource requirements, that the worksteps from these two classes can be distinguished. Therefore, all of the worksteps are placed into one cluster. The worksteps are described as coming from two distinct classes because the worksteps in class 1 are from a production system that will have its master file moved from tape to disk, while the master file used by the worksteps in class 2 will remain on tape. Therefore, the types of resources required by the worksteps from this class will change rather abruptly. Figure 1b shows a scatter plot of the clusters after predicting the future resource requirements of these worksteps. Since the resource requirements of the worksteps in class 2 are expected to remain essentially constant they are plotted in the same position. The worksteps in class 1 are presented as a new cluster with a significantly lower number of tape EXCP’s and a correspondingly higher number of disk EXCP’s. These plots are not meant to imply that there
will be a one for one conversion of tape EXCP's to disk EXCP's, but rather that most of the I/O that these worksteps perform will be performed to disk. The exact number of disk EXCP's executed will depend upon a number of factors such as the buffer size that is used, the disk access method that is used, expected changes in the size of the master file, and changes in the number of records to be processed by each workstep. Each of these factors will influence the number of disk EXCP's that a workstep will perform. The number of records to be processed by each workstep may change for several reasons. First, the system will become more heavily used due to increases in the application load. This would increase the amount of I/O performed per day. On the other hand, once the data file is placed on disk, and is thus more accessible, one might decide to run a larger number of worksteps each of which processes a smaller number of records, thereby decreasing the number of disk EXCP's per workstep. Each of these factors depends upon factors to be decided upon before the system conversion can be made and thus can be used in predicting the system load.

The processing load at this installation is subject to a variety of external influences. The processing carried on at this installation is used to support the activities of a large number of divisions throughout the parent organization. Therefore, the processing load on the computer will be effected by management decisions on the initiation or curtailment of activities throughout the organization. In fact, a recent decision by management to reduce a specific activity of one of the divisions will have the effect of reducing the number of records processed by one of the application programs by approximately one third. There is no way that such a change in the processing requirements of the production system could be predicted from data observed on the machine. However, the external factors influencing this change are well understood and their effects can be very accurately determined well in advance. Use of this external information is in fact the only way in which the load on the system due to this application can be accurately predicted.

Figures 2a and 2b represent a cluster that contains many of the program development worksteps. This cluster is composed of a large number of worksteps drawn from a number of sources. Based on observations carried out over a period of time it has been observed that the amount of load attributable to the program development cluster has been increasing. This increase in load is due to an increase in the number and size of the program development worksteps.

This cluster's size and position can be predicted using trend analysis. This is a case in which the position of the cluster drifts due to the movement of most of the data points in the cluster. This movement can be seen when the clusters in Figures 2a and 2b are compared. The cluster in Figure 2b contains more points that the cluster in Figure 2a. This is due to the expected increase in the number of program development worksteps that will be executed by the system.

It should be noted that as the cluster mean drifts and the size of the cluster increases the variance of the data points in the cluster increases as well. This occurs because not all of the worksteps are expected to change in precisely the same manner causing the data points to become more spread out in the seven dimensional space.

When observing this cluster over a long period of time, it becomes clear that the trend is definitely one of constant growth in terms of both the number of worksteps and the size of the worksteps. This is not meant to imply that the rate of increase is absolutely constant. There is some random variation in the number of program development worksteps executed in a given time period. However, this type of random variation is commonly encountered in trend analysis studies and is easily handled.

There is also a rather strong oscillatory component to the workload. While some of the production systems are run on
TABLE I.—Amount of Load Attributable to Various Clusters

<table>
<thead>
<tr>
<th>Cluster</th>
<th>Percent of workload in normal environment</th>
<th>Percent of workload in periodic environment</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>51</td>
<td>10</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>15</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>84</td>
</tr>
</tbody>
</table>

When the set of benchmark programs and the system's requirements are released to the vendors there will be two benchmark experiments to be run. First, a set of benchmark programs representing the normal processing load on the system will be run and the results compared. Second, there will be a requirement that the system to be purchased must be able to execute a representative portion of one of the periodic worksteps in less than a specified amount of time. This has to be done because the system has two operating modes and a new system must be able to handle two very distinct types of loads. It is quite likely that if the worksteps from the periodic systems were combined with the rest of the worksteps into one benchmark then the results that would be obtained from such a benchmark would most likely be rather inaccurate.

CONCLUDING REMARKS

In this paper we consider the problem of workload prediction and note that an accurate prediction can only be made by considering the changes in the individual segments of the workload. For this purpose the segments, or natural groupings, of the workload may be identified using clustering, and then the way components, or clusters, are going to change can be taken into account in the prediction.

The future workload is often affected to a significant degree by external factors. It is crucial that such external factors be taken into account when making the workload predictions by considering the new applications or changes to the modes of operation as well as the effects of external factors on the applications.

REFERENCES
