THE UNIVERSITY OF NAIROBI
SCHOOL OF COMPUTING AND INFORMATICS

MACHINE LEARNING TECHNIQUES FOR OPTIMIZING THE PROVISION OF STORAGE RESOURCES IN CLOUD COMPUTING INFRASTRUCTURE AS A SERVICE (IaaS): A COMPARATIVE STUDY

BY

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DECLARATION

This research project report is my original work and has not been presented for any award in any other University.

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This research project report has been submitted in partial fulfillment of the requirements of the Masters of Science in Computer Science of The University of Nairobi with my approval as the University Supervisor.

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ABSTRACT

Cloud computing is a very popular field at present which is growing very fast and the future of the field seems really wide. With progressive spotlight on cloud computing as a possible solution for a flexible, on-demand computing infrastructure for lots of applications, many companies and unions have started using it. Obviously, cloud computing has been recognized as a model for supporting infrastructure, platform and software services. Within cloud systems, massive distributed data center infrastructure, virtualized physical resources, virtualized middleware platform such as VMware as well as applications are all being provided and consumed as services. The cloud clients should get good and reliable services from a provider and the provider should allocate the resources in a proper way so as to render good services to a client. This brings about the problem of optimization where clients request for more services than they actually require leading to wastage of the cloud storage resource .This demands for optimization both on the part of the client and the cloud service provider. This has lead to increased research in the various techniques that can be used for resource allocation within cloud services. This research focuses on the analysis of machine learning as a technique that can be used to predict the cloud storage service request patterns from the clients. The research focuses on a review of machine learning as a technique that can be used to predict and therefore optimize the user storage resource demand and usage for the case of cloud computing storage IaaS. Data on cloud storage resource usage was subjected to experiments using machine learning techniques so as to determine which give the most accurate prediction. Some of these machine learning techniques to be reviewed in this research include linear regression, artificial neural networks (ANN), support vector machines (SVM).From the experiments done in this research, it can be concluded that the use of support vector machine algorithm (SVM) proves to be the best algorithm for learning the storage resource usage patterns and predicting their future usage so as to enable better resource budgeting.

LIST OF ABREVIATIONS

IaaS-Infrastructure as a Service

PaaS-Platform as a Service

SaaS-Software as a Service

API-application programming interface

WWW-world wide web

RTE-run time environment

FLOP-floating point operations per second

ML-machine learning

SVM-support vector machine

DNS-domain name server

SLA-Service Level Agreements

AMAZON E2C-Amazon elastic compute cloud

CRAIG-cloud resource allocation game

SVM-support vector machine

CSV-comma separated values

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CHAPTER ONE : INTRODUCTION

1.0 Background

Cloud computing is a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources such as networks, servers, storage, applications, and services that can be rapidly provisioned and released with minimal management effort or service provider interaction (NIST).

Cloud Computing has become one of the popular buzzwords in the IT area after Web2.0. This is not a new technology, but the concept that binds different existing technologies altogether including Grid Computing, Utility Computing, distributed system, virtualization and other mature technique.

Cloud computing systems provide environments to enables resource provision in terms of scalable infrastructures, middleware, application development platforms and value-added business applications. Software as a Service (SaaS), Platform as a Service (PaaS) and Infrastructure as a Service (IaaS) are three basic service layer.

SaaS: The capability provided to the consumer is to use the provider’s applications running on a cloud infrastructure. The applications are accessible from various client devices through either a thin client interface, such as a web browser (e.g., web-based email), or a program interface. The consumer does not manage or control the underlying cloud infrastructure including network, servers, operating systems, storage, or even individual application capabilities, with the possible exception of limited user-specific application configuration settings (NIST).

PaaS: The capability provided to the consumer is to deploy onto the cloud infrastructure consumer-created or acquired applications created using programming languages, libraries, services, and tools supported by the provider. The consumer does not manage or control the underlying cloud infrastructure including network, servers, operating systems, or storage, but has control over the deployed applications and possibly configuration settings for the application-hosting environment (NIST).

IaaS: The capability provided to the consumer is to provision processing, storage, networks, and other fundamental computing resources where the consumer is able to deploy and run arbitrary software, which can include operating systems and applications. The consumer does not manage or control the underlying cloud infrastructure but has control over operating systems, storage, and deployed applications; and possibly limited control of select networking components (NIST).

Examples of infrastructure services provider on a global scale include Rackspace, GoGrid, Amazon EC2, Microsoft Azure Platform, Terremark Cloud Storage, and more. Infrastructure services address the problem of properly equipping data centers by assuring storage computing power when needed.

Various resources are available within the cloud computing environment. Resource consumption by an application in the form of CPU time, disk space, amount of memory and network bandwidth is a useful set of information when available before allocating resources. The need to know resource consumption has the benefit of helping cloud service providers in resource optimization

In cloud computing, Resource Allocation is the process of assigning available resources to the needed cloud applications over the internet. Resource allocation starves services if the allocation is not managed precisely. Resource provisioning solves that problem by allowing the service providers to manage the resources for each individual module (mahendra et. al, 2013).

An optimal Resource Allocation Strategy should avoid the following criteria i.e. Resource Contention in which demand exceeds supply for a shared resource, such as memory, CPU, network or storage. In modern IT, where cost cuts are the norm, addressing resource contention is a top priority. The main concern with resource contention is the performance degradation that occurs as a result. Second Criteria is Scarcity of Resource which happens when there are limited resources and the demand for resources is high. In such situation user can not avail facility of resource. Third criteria are Resource Fragmentation –In these criteria resources are isolated. There would be enough resources but cannot allocate it to the needed application due to fragmentation into small entities. If fragmentation is done into big entities then we can use it optimum. Forth criteria is Over Provisioning – Over provisioning arises when the application gets surplus resources than the demanded one. Due to this, the investment is high and revenue is low. The fifth criterion is Under Provisioning, which occurs when the application is assigned with fewer numbers of resources than it demanded (Mahendra et. al, 2013).

In the Kenyan context, Safaricom limited is one of the companies offering cloud computing services. With cloud services, businesses of all sizes are able to reap the benefits of not having to deploy physical infrastructure in their premises such as file and e-mail servers, storage systems and software. Access to these IT resources means hassle-free collaboration between business partners and employees by using simple online applications. The cloud services offered by Safaricom include

- Infrastructure as a Service
- Data Centre
- Storage Services
- Platform as a Service
- Hosted Applications
- Software as a Service
- Data Archiving
- Backup and Recovery

It is paramount for any organization involved in cloud computing service delivery to identify the clients' resource utilization patterns and map this against the available resources so as to be able to justify their claims when advising clients on their actual cloud resource requirements and in term provide better management of their cloud computing resources. This will enable savings on the part of the customer since they can be accurately advised on their specific resource requirements hence more informed resource requests on their part, and on the side of the cloud service provider, they can be able to optimally plan for the resources available. The aim of this study is to do a comparative study of machine learning techniques and find out which one yields the most accurate and optimal prediction for the case of predicting storage resource usage for the case of Cloud computing IaaS .This could be used to advice clients on their resource usage as compared to resource requests for the case of IaaS. The solution is to use the usage patterns of clients in order to suggest the best machine learning technique that can predict client future storage resource usage and be based on this the provider can achieve better storage resource investment plan and also be able to advise clients on they can make more efficient resource acquisition.

1.1 Problem statement

The main problem that is to be addressed by this research is that of over provisioning of resources which include storage by a cloud IaaS provider [19].Over provisioning arises when the application gets surplus resources than the demanded ones (vinothina et al.).

As more companies put workloads on Amazon Web Services or other public cloud platforms, many are paying for more cloud than they need. That over provisioning is the problem. [23]. Over provisioning arises when a client requests for much more resources (processor, RAM and storage) than what they actually use. This is a problem for organizations offering IaaS in the sense that some resources go unused. It is also a problem for the clients because they unknowingly end up paying for more processor and storage resources than they use.

1.2 The goal of the study

The project aims to find out the appropriate machine learning techniques to predict client cloud storage resource usage.

1.2.1 Specific objectives

The specific objectives of the research were as follows:-

i. Identify various machine learning techniques.

ii. Select some machine learning techniques.

iii. Collect real test data.

iv. Simulate additional test data.

v. Run machine learning techniques on the combined test data.

vi. Analyze the results of the machine learning techniques.

vii. Compare the performance of the machine learning techniques.

viii. Complete the report.

1.3 Research question

Which machine learning technique amongst linear regression, support vector machine (SVM) and artificial neural networks (ANN) gives the best prediction for a user's storage resource request verses their usage?

1.4 Scope of the study

The research will be limited to a review of three machine learning techniques that is linear regression, support vector machine and artificial neural networks and the metrics which will be used for the evaluation include, Mean Absolute Percentage Error, Root Mean Square Error, coefficient of variation and comparison between actual verses predicted data.

1.5 Significance

Cloud computing is rapidly taking shape all over the world and it is paramount for us to start thinking how resources are going to be provisioned and allocated in an efficient way based on some forecasting or prediction mechanism.

On a more specific note, this research will contribute to the body of knowledge that the software developers for applications that are used for cloud computing resources management and cloud service providers such as Safaricom Ltd. can benefit from the research by understanding the best machine learning technique that can be used in prediction of resource usage for the case of cloud IaaS.

1.6 Contributions

This research has brought to light that indeed machine learning can be used to predict resource usage for the case of cloud computing storage resource usage and more specifically, Support Vector Machine (SVM) algorithm is the most suitable for cases similar to that covered in this research.

1.7 Organization of the report

This research report begins by giving an overview of the cloud computing environment in the first chapter and the highlights the problem of over provisioning as a major challenge. The second chapter details an overview of the various machine learning techniques focusing on three, that is linear regression, support vector and time series algorithms. It also looks at the various tools that can be used for machine learning. The third chapter gives an overview of how the research was conducted in terms of the methodology, how the data was prepared and how the experiments were done. The fourth chapter deals with the analysis of the results from each of the machine learning algorithms and an analysis of their accuracy in making the predictions for client resource usage. The fifth chapter is on the conclusions and recommendations that the researcher came up with after conducting the research

CHAPTER TWO : LITERATURE REVIEW

2.0 Introduction

This chapter focuses on cloud computing resources, resource allocation models and methods, machine learning tools and algorithms, profiling and modeling resource usage, and other related works. Cloud computing offers three main services which are PaaS, SaaS and Iaas. There is lack of an appropriate machine learning technique that can be used to predict storage resource consumption for the case of IaaS cloud computing service. Machine learning can be used to predict these storage resource usage based on previous client usage patterns. Cloud computing can be offered using various deployment models and there are various players involved in offering cloud computing service. These have been conclusively discussed in the literature review. Various resource allocation models are reviewed so as to get an overview of the various resources and the methods that are used to allocate these resources. A review on machine learning is also done so as to give a firm background on the various machine learning algorithms and modeling techniques, their strengths, weaknesses and applications.

The benefits of this include a better awareness on storage resource usage for future planning on the part of the organizations Cloud computing services and hence saving on costs as well as better client advisory on future requirements when they request for storage service requests thereby saving clients from unnecessary additional costs. The poor performance results produced by statistical estimation models have flooded the estimation area for over the last decade. Their inability to handle categorical data, cope with missing data points, spread of data points and most importantly lack of reasoning capabilities has triggered an increase in the number of studies using non-traditional methods like machine learning techniques (Yogesh Singh, et. al). The area of machine learning draws on concepts from diverse fields such as statistics, artificial intelligence, philosophy, information theory, biology, cognitive science, computational complexity and control theory. In this case the researcher picked on Safaricom limited as a local cloud computing service provider and corporate organizations it provides this services to as the clients for the case of IaaS. If not well managed, a cloud service provider may end up under-utilizing the available resources on his part and the cloud client may end up paying for more services than they actually require. This can be both detrimental to the client in terms of unnecessary cost and to the service provider in terms of resource wastages.

2.1 Cloud computing

2.1.1 Definition of cloud computing?

Cloud computing is a model for enabling convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction. This cloud model promotes availability and is composed of five essential characteristics (On-demand self-service, Broad network access, Resource pooling, Rapid elasticity, Measured Service); three service models (Cloud Software as a Service (SaaS), Cloud Platform as a Service (PaaS), Cloud Infrastructure as a Service (IaaS)); and, four deployment models (Private cloud, Community cloud, Public cloud, Hybrid cloud). Key enabling technologies include: (1) fast wide-area networks, (2) powerful, inexpensive server computers, and (3) high-performance virtualization for commodity hardware (NIST).

2.1.2 Cloud computing service models

Software as a service (SaaS)

The capability provided to the consumer is to use the provider's applications running on a cloud infrastructure. The applications are accessible from various client devices through either a thin client interface, such as a web browser (e.g., web-based email), or a program interface. The consumer does not manage or control the underlying cloud infrastructure including network, servers, operating systems, storage, or even individual application capabilities, with the possible exception of limited user-specific application configuration settings (NIST).

Platform as a service (PaaS)

The capability provided to the consumer is to deploy onto the cloud infrastructure consumer-created or acquired applications created using programming languages, libraries, services, and tools supported by the provider. The consumer does not manage or control the underlying cloud infrastructure including network, servers, operating systems, or storage, but has control over the deployed applications and possibly configuration settings for the application-hosting environment (NIST).

With PaaS the following benefits can be achieved:

- Develop applications and get to market faster
- Deploy new web applications to the cloud in minutes
- Reduce complexity with middleware as a service

Infrastructure as a service (IaaS)

IaaS: The capability provided to the consumer is to provision processing, storage, networks, and other fundamental computing resources where the consumer is able to deploy and run arbitrary software, which can include operating systems and applications. The consumer does not manage or control the underlying cloud infrastructure but has control over operating systems, storage, and deployed applications; and possibly limited control of select networking components (NIST).

Examples of infrastructure services provider include IBM BlueHouse, VMWare, Amazon EC2, Microsoft Azure Platform, Sun ParaScale Cloud Storage, and more. Infrastructure services address the problem of properly equipping data centers by assuring computing power when needed.

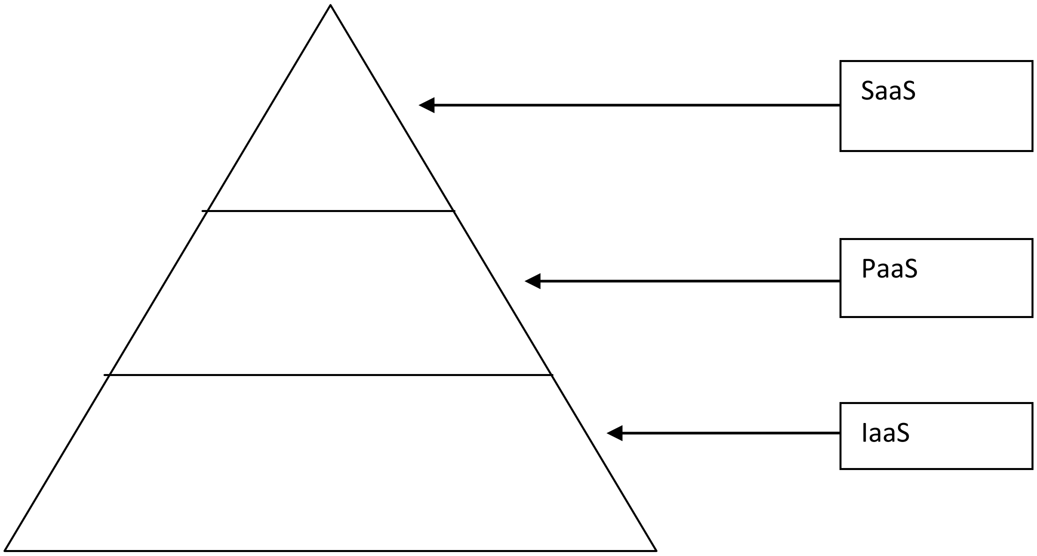


Figure 1-Cloud systems architecture

Benefits of cloud computing

The advantages of "renting" these "virtual resources" over traditional on-premise IT includes:

- On demand and elastic services—quickly scale up or down
- Self-service, automated provisioning and de-provisioning
- Reduced costs from economies of scale and resource pooling
- Pay-for-use—costs based on metered service usage

In the most basic cloud-service model, providers of IaaS offer computers - physical or (more often) virtual machines - and other resources. (A hypervisor, such as Xen or KVM, runs the virtual machines as guests. Pools of hypervisors within the cloud operational support-system can support large numbers of virtual machines and the ability to scale services up and down according to customers' varying requirements.) IaaS clouds often offer additional resources such as a virtual-machine disk image library, raw (block) and file-based storage, firewalls, load balancers, IP addresses, virtual local area networks (VLANs), and software bundles. IaaS cloud providers supply these resources on-demand from their large pools installed in data centers. For wide-area connectivity, customers can use either the Internet or carrier clouds (dedicated virtual private networks).

To deploy their applications, cloud users install operating-system images and their application software on the cloud infrastructure. In this model, the cloud user patches and maintains the operating systems and the application software. Cloud providers typically bill IaaS services on a utility computing basis: cost reflects the amount of resources allocated and consumed.

Examples of IaaS providers include: Amazon EC2, AirVM, Azure Services Platform, DynDNS, Google Compute Engine, HP Cloud, iland, Joyent, LeaseWeb, Linode, NaviSite, Oracle Infrastructure as a Service, Rackspace, ReadySpace Cloud Services, ReliaCloud, SAVVIS, SingleHop, and Terremark

2.1.3 Cloud deployments models

Cloud services can be deployed in different ways, depending on the organizational structure and the provisioning location. Four deployment models are usually distinguished, namely public, private, community and hybrid cloud service usage.

Public Cloud

The deployment of a public cloud computing system is characterized on the one hand by the public availability of the cloud service offering and on the other hand by the public network that is used to communicate with the cloud service. The cloud services and cloud resources are procured from very large resource pools that are shared by all end users. These IT factories, which tend to be specificaly built for running cloud computing systems, provision the resources precisely according to required quantities. By optimizing operation, support, and maintenance, the cloud provider can achieve significant economies of scale, leading to low prices for cloud resources. In addition, public cloud portfolios employ techniques for resource optimization; however, these are transparent for end users and represent a potential threat to the security of the system. If a cloud provider runs several datacenters, for instance, resources can be assigned in such a way that the load is uniformly distributed between all centers. Some of the best-known examples of public cloud systems are Amazon Web Services (AWS) containing the Elastic Compute Cloud (EC2) and the Simple Storage Service (S3) which form an IaaS cloud offering and the Google App Engine with provides a PaaS to its customers. The customer relationship management (CRM) solution Salesforce.com is the best-known example in the area of SaaS cloud offerings.

Private Cloud

Private cloud computing systems emulate public cloud service offerings within an organization's boundaries to make services accessible for one designated organization. Private cloud computing systems make use of virtualization solutions and focus on consolidating distributed IT services often within data centers belonging to the company. The chief advantage of these systems is that the enterprise retains full control over corporate data, security guidelines, and system performance. In contrast, private cloud offerings are usually not as large-scale as public cloud offerings resulting in worse economies of scale.

Community Cloud

In a community cloud, organizations with similar requirements share a cloud infrastructure. It may be understood as a generalization of a private cloud, a private cloud being an infrastructure which is only accessible by one certain organization.

Hybrid Cloud

A hybrid cloud service deployment model implements the required processes by combining the cloud services of different cloud computing systems, e.g. private and public cloud services. The hybrid model is also suitable for enterprises in which the transition to full outsourcing has already been completed, for instance, to combine community cloud services with public cloud services.

2.1.4 Cloud environment roles

In cloud environments, individual roles can be identified similar to the typical role distribution in Service Oriented Architectures and in particular in (business oriented) Virtual Organizations. As the roles relate strongly to the individual business models it is imperative to have a clear definition of the types of roles involved in order to ensure common understanding.

Cloud Providers offer clouds to the customer – either via dedicated APIs (PaaS), virtual machines and / or direct access to the resources (IaaS). Hosts of cloud enhanced services (SaaS) are typically referred to as Service Providers, though there may be ambiguity between the terms Service Provider and Cloud Provider.

Cloud Resellers aggregate cloud platforms from cloud providers to either provide a larger resource infrastructure to their customers or to provide enhanced features. This relates to community clouds in so far as the cloud aggregators may expose a single interface to a merged cloud infrastructure. They will match the economic benefits of global cloud infrastructures with the understanding of local customer needs by providing highly customized, enhanced offerings to local companies (especially SME's) and world-class applications in important European industry sectors. Similar to the software and consulting industry, the creation of European cloud partner ecosystems will provide significant economic opportunities in the application domain – first, by mapping emerging industry requests into innovative solutions and second by utilizing these innovative solutions by European companies in the global marketplace.

Cloud Adopters or (Software / Services) Vendors enhance their own services and capabilities by exploiting cloud platforms from cloud providers or cloud resellers. This enables them to e.g. provide services that scale to dynamic demands – in particular new business entries who cannot estimate the uptake / demand of their services as yet. The cloud enhanced services thus effectively become software as a service.

Cloud Consumers or Users make direct use of the cloud capabilities – as opposed to cloud resellers and cloud adopters, however, not to improve the services and capabilities they offer, but to make use of the direct results, i.e. either to execute complex computations or to host a flexible data set. Note that this involves in particular larger enterprises which outsource their in house infrastructure to reduce cost and efforts.

Cloud Tool Providers do not actually provide cloud capabilities, but supporting tools such as programming environments, virtual machine management etc.

Cloud Auditor - A third-party (often accredited) that conducts independent assessments of cloud environments assumes the role of the cloud auditor. The typical responsibilities associated with this role include the evaluation of security controls, privacy impacts, and performance. The main purpose of the cloud auditor role is to provide an unbiased assessment (and possible endorsement) of a cloud environment to help strengthen the trust relationship between cloud consumers and cloud providers.

Cloud Broker - This role is assumed by a party that assumes the responsibility of managing and negotiating the usage of cloud services between cloud consumers and cloud providers. Mediation services provided by cloud brokers include service intermediation, aggregation, and arbitrage.

Cloud Carrier - The party responsible for providing the wire-level connectivity between cloud consumers and cloud providers assumes the role of the cloud carrier. This role is often assumed by network and telecommunication providers (NIST).

2.1.5 Cloud characteristics

Cloud computing is a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction. The essential characteristics for cloud computing includes the ones highlighted below.

On-demand self-service. A consumer can unilaterally provision computing capabilities, such as server time and network storage, as needed automatically without requiring human interaction with each service provider.

Broad network access. Capabilities are available over the network and accessed through standard mechanisms that promote use by heterogeneous thin or thick client platforms (e.g., mobile phones, tablets, laptops, and workstations).

Resource pooling. The provider's computing resources are pooled to serve multiple consumers using a multi-tenant model, with different physical and virtual resources dynamically assigned and reassigned according to consumer demand. There is a sense of location independence in that the customer generally has no control or knowledge over the exact location of the provided resources but may be able to specify location at a higher level of abstraction (e.g., country, state, or datacenter). Examples of resources include storage, processing, memory, and network bandwidth.

Rapid elasticity. Capabilities can be elastically provisioned and released, in some cases automatically, to scale rapidly outward and inward commensurate with demand. To the consumer, the capabilities available for provisioning often appear to be unlimited and can be appropriated in any quantity at any time.

Measured service. Cloud systems automatically control and optimize resource use by leveraging a metering capability1 at some level of abstraction appropriate to the type of service (e.g., storage, processing, bandwidth, and active user accounts). Resource usage can be monitored, controlled, and reported, providing transparency for both the provider and consumer of the utilized service.

2.1.6 Providers of cloud Infrastructure services

While many are using custom platforms, where they have written their own code to manage their virtual servers, a lot are using already available frameworks or turnkey solutions to power their cloud offerings. If an organization is looking to start offering cloud services there is a jungle of different platforms available, both commercial and open source, that can either help it get started or deliver to the organization a complete solution tailored to fit the organization's objectives

2.1.6.1 Infrastructure Services offered by cloud Providers

The objective of this section is to review the different infrastructure services offered by IaaS cloud providers with an emphasis on storage services.

i. AmazonAWS

Amazon AWS is the most popular cloud hosting provider. Amazon offers compute services in the form of Amazon EC2 and storage services in the form of S3, EBS and simple DB Amazon S3. Amazon offers servers with up to 117GB memory and 16 CPU cores. Amazon also offers specialized GPU based machines for intense scientific computation which none of their competitors offer. During 2012 they introduced servers with SSD disks for high performance. Ethernet networks with 10GBps, 1Gbps and 100Mbps. Virtual Private Clouds and Direct Connections are available which provide advanced capabilities to integrate private networks with AWS. Amazon offer data storage via S3 and EBS as well as several newer services. Amazon is constantly releasing exciting new services for data storage and processing so they are evolving rapidly to maintain their leadership position in the industry.

Amazon compute services

Amazon Elastic Compute Cloud (Amazon EC2) is a web service that provides resizable compute capacity in the cloud. It is designed to make web-scale computing easier for developers.

Amazon EC2 Functionality

Amazon EC2 presents a true virtual computing environment, allowing the client to use web service interfaces to launch instances with a variety of operating systems, load them with client's custom application environment, manage your network's access permissions, and run the image using as many or few systems as the client desires.

(SOURCE: http://aws.amazon.com/)

Standard Instances on Amazon EC2

First Generation

First generation (M1) Standard instances provide customers with a balanced set of resources and a low cost platform that is well suited for a wide variety of applications.

- M1 Small Instance (Default) 1.7 GiB of memory, 1 EC2 Compute Unit (1 virtual core with 1 EC2 Compute Unit), 160 GB of local instance storage, 32-bit or 64-bit platform
- M1 Medium Instance 3.75 GiB of memory, 2 EC2 Compute Units (1 virtual core with 2 EC2 Compute Units each), 410 GB of local instance storage, 32-bit or 64-bit platform
- M1 Large Instance 7.5 GiB of memory, 4 EC2 Compute Units (2 virtual cores with 2 EC2 Compute Units each), 850 GB of local instance storage, 64-bit platform
- M1 Extra Large Instance 15 GiB of memory, 8 EC2 Compute Units (4 virtual cores with 2 EC2 Compute Units each), 1690 GB of local instance storage, 64-bit platform

Second Generation

Second generation (M3) Standard instances provide customers with a balanced set of resources and a higher level of processing performance compared to First Generation Standard instances. Instances in this family are ideal for applications that require higher absolute CPU and memory performance.

- M3 Extra Large Instance 15 GiB of memory, 13 EC2 Compute Units (4 virtual cores with 3.25 EC2 Compute Units each), EBS storage only, 64-bit platform
- M3 Double Extra Large Instance 30 GiB of memory, 26 EC2 Compute Units (8 virtual cores with 3.25 EC2 Compute Units each), EBS storage only, 64-bit platform

Micro Instances

Micro instances (t1.micro) provide a small amount of consistent CPU resources and allow one to increase CPU capacity in short burst when additional cycles are available. They are well suited for lower throughput applications and web sites that require additional compute cycles periodically.

- Micro Instance 613 MiB of memory, up to 2 ECUs (for short periodic bursts), EBS storage only, 32-bit or 64-bit platform

High-Memory Instances

Instances of this family offer large memory sizes for high throughput applications, including database and memory caching applications.

- High-Memory Extra Large Instance 17.1 GiB memory, 6.5 ECU (2 virtual cores with 3.25 EC2 Compute Units each), 420 GB of local instance storage, 64-bit platform
- High-Memory Double Extra Large Instance 34.2 GiB of memory, 13 EC2 Compute Units (4 virtual cores with 3.25 EC2 Compute Units each), 850 GB of local instance storage, 64-bit platform
- High-Memory Quadruple Extra Large Instance 68.4 GiB of memory, 26 EC2 Compute Units (8 virtual cores with 3.25 EC2 Compute Units each), 1690 GB of local instance storage, 64-bit platform

High-CPU Instances

Instances of this family have proportionally more CPU resources than memory (RAM) and are well suited for compute-intensive applications.

- High-CPU Medium Instance 1.7 GiB of memory, 5 EC2 Compute Units (2 virtual cores with 2.5 EC2 Compute Units each), 350 GB of local instance storage, 32-bit or 64-bit platform
- High-CPU Extra Large Instance 7 GiB of memory, 20 EC2 Compute Units (8 virtual cores with 2.5 EC2 Compute Units each), 1690 GB of local instance storage, 64-bit platform

Cluster Compute Instances

Instances of this family provide proportionally high CPU resources with increased network performance and are well suited for High Performance Compute (HPC) applications and other demanding network-bound applications.

- Cluster Compute Eight Extra Large 60.5 GiB memory, 88 EC2 Compute Units, 3370 GB of local instance storage, 64-bit platform, 10 Gigabit Ethernet

High Memory Cluster Instances

Instances of this family provide proportionally high CPU and memory resources with increased network performance, and are well suited for memory-intensive applications including in-memory analytics, graph analysis, and scientific computing.

- High Memory Cluster Eight Extra Large 244 GiB memory, 88 EC2 Compute Units, 240 GB of local instance storage, 64-bit platform, 10 Gigabit Ethernet

Cluster GPU Instances

Instances of this family provide general-purpose graphics processing units (GPUs) with proportionally high CPU and increased network performance for applications benefitting from highly parallelized processing, including HPC, rendering and media processing applications. While Cluster Compute Instances provide the ability to create clusters of instances connected by a low latency, high throughput network, Cluster GPU Instances provide an additional option for applications that can benefit from the efficiency gains of the parallel computing power of GPUs over what can be achieved with traditional processors.

- Cluster GPU Quadruple Extra Large 22 GiB memory, 33.5 EC2 Compute Units, 2 x NVIDIA Tesla “Fermi” M2050 GPUs, 1690 GB of local instance storage, 64-bit platform, 10 Gigabit Ethernet

High I/O Instances

Instances of this family provide very high disk I/O performance and are ideally suited for many high performance database workloads. High I/O instances provide SSD-based local instance storage, and also provide high levels of CPU, memory and network performance.

- High I/O Quadruple Extra Large 60.5 GiB memory, 35 EC2 Compute Units, 2 * 1024 GB of SSD-based local instance storage, 64-bit platform, 10 Gigabit Ethernet

High Storage Instances

Instances of this family provide proportionally higher storage density per instance, and are ideally suited for applications that benefit from high sequential I/O performance across very large data sets. High Storage instances also provide high levels of CPU, memory and network performance.

- High Storage Eight Extra Large 117 GiB memory, 35 EC2 Compute Units, 24 * 2 TB of hard disk drive local instance storage, 64-bit platform, 10 Gigabit Ethernet

EC2 Compute Unit (ECU) – One EC2 Compute Unit (ECU) provides the equivalent CPU capacity of a 1.0-1.2 GHz 2007 Opteron or 2007 Xeon processor.

(SOURCE: http://aws.amazon.com/)

Amazon storage services

Amazon offers storage services in the form of S3, EBS and simple DB**Amazon S3.**

Amazon S3: Amazon S3 provides a simple web-services interface that can be used to store and retrieve any amount of data, at any time, from anywhere on the web. It gives any developer access to the same highly scalable, reliable, secure, fast, inexpensive infrastructure that Amazon uses to run its own global network of web sites. The service aims to maximize benefits of scale and to pass those benefits on to developers.

Amazon EBS

Amazon Elastic Block Store (Amazon EBS) provides persistent block level storage volumes for use with Amazon EC2 instances in the AWS Cloud. Each Amazon EBS volume is automatically replicated within its Availability Zone to protect users from component failure, offering high availability and durability. Amazon EBS volumes offer the consistent and low-latency performance needed to run your workloads. With Amazon EBS, you can scale your usage up or down within minutes – all while paying a low price for only what users' provision.

Simple DB

Amazon SimpleDB is a highly available and flexible non-relational data store that offloads the work of database administration. Developers simply store and query data items via web services requests and Amazon SimpleDB does the rest. Unbound by the strict requirements of a relational database, Amazon SimpleDB is optimized to provide high availability and flexibility, with little or no administrative burden. Behind the scenes, Amazon SimpleDB creates and manages multiple geographically distributed replicas of your data automatically to enable high availability and data durability. The service charges users only for the resources actually consumed in storing client's data and serving client requests. Clients can change your data model on the fly, and data is automatically indexed for clients. With Amazon SimpleDB, clients can focus on application development without worrying about infrastructure provisioning, high availability, software maintenance, schema and index management, or performance tuning. Multiple attributes of Amazon SimpleDB make it an attractive data store for data logs:

- **Central, with High Availability** – If client's data logs were previously being trapped locally in multiple devices/objects, applications, or process silos, you'll enjoy the benefit of being able to access your data centrally in one place in the cloud. What's more, Amazon SimpleDB automatically and geo-redundantly replicates client's data to ensure high availability. This means that unlike a centralized on-premise solution, you're not creating a single point of failure with Amazon SimpleDB, and your data will be there when you need it. All of the data can be stored via web services requests with one solution and then accessed by any device.
- **Zero Administration** – You store your data items with simple web services requests and Amazon Web Services takes care of the rest. The set it and forget it nature of the service means you aren't spending time on database management in order to store and maintain data logs.
- **Cost-efficient** – Amazon SimpleDB charges inexpensive prices to store and query your data logs. Since you are paying as you go for only the resources you consume, you don't

need to do your own capacity planning or worry about database load. The service simply responds to request volume as it comes and goes, charging you only for the actual resources consumed.

- **Reduced Redundancy Storage (RRS)**

  Reduced Redundancy Storage (RRS) is a storage option within Amazon S3 that enables customers to reduce their costs by storing non-critical, reproducible data at lower levels of redundancy than Amazon S3's standard storage. It provides a cost-effective, highly available solution for distributing or sharing content that is durably stored elsewhere, or for storing thumbnails, transcoded media, or other processed data that can be easily reproduced. The RRS option stores objects on multiple devices across multiple facilities, providing 400 times the durability of a typical disk drive, but does not replicate objects as many times as standard Amazon S3 storage, and thus is even more cost effective.

- **Amazon Glacier**

  Amazon S3 enables you to utilize Amazon Glacier's extremely low-cost storage service as a storage option for data archival. Amazon Glacier stores data for as little as $0.01 per gigabyte per month, and is optimized for data that is infrequently accessed and for which retrieval times of several hours are suitable. Examples include digital media archives, financial and healthcare records, raw genomic sequence data, long-term database backups, and data that must be retained for regulatory compliance.

- Like Amazon S3's other storage options (Standard or Reduced Redundancy Storage), objects stored in Amazon Glacier using Amazon S3's APIs or Management Console have an associated user-defined name. You can get a real-time list of all of your Amazon S3 object names, including those stored using the Amazon Glacier option, using the Amazon S3 LIST API. Objects stored directly in Amazon Glacier using Amazon Glacier's APIs cannot be listed in real-time, and have a system-generated identifier rather than a user-defined name. Because Amazon S3 maintains the mapping between your user-defined object name and the Amazon Glacier system-defined identifier, Amazon S3 objects that are stored using the Amazon Glacier option are only accessible through Amazon S3's APIs or the Amazon S3 Management Console

Storage allocation policies

With Amazon S3 the client pays only for what they use. This implies that the memory allocation is dynamic. There is no minimum fee. The charges are based on the location of the cloud client's S3 bucket. Below is sample storage charging for USA western region.

Table 1: Storage allocation policies for Amazon S3

STORAGE CAPACITY	STANDARD STORAGE	REDUCED REDUNDANCY STORAGE	GLACIER STORAGE
First 1 TB / month	$0.094 / GB	$0.075 / GB	$0.011 / GB
Next 49 TB / month	$0.084 / GB	$0.068 / GB	$0.011 / GB
Next 450 TB / month	$0.064 / GB	$0.051 / GB	$0.011 / GB
Next 500 TB / month	$0.059 / GB	$0.047 / GB	$0.011 / GB
Next 4000 TB / month	$0.055 / GB	$0.044 / GB	$0.011 / GB
Over 5000 TB / month	$0.047 / GB	$0.038 / GB	$0.011 / GB

(http://aws.amazon.com/s3/details/)

ii. Rackspace

Rackspace is a solid, established and growing company that has been a pioneer in the Cloud Computing industry offering service with up to 30GB memory and 8 CPU cores, however their network speeds, even for their fastest servers are less than 1Gbps which could severely limit performance, especially when deploying clusters of computers that reply on high speed communication. They developed and operate their service using OpenStack which is available for companies to use internally. This offers unique options for companies that want to run a hybrid environment with in-house and cloud-hosted computing resources. Examples of usage scenarios could be where internal computing is supplemented by cloud computing for large projects or where applications are prototyped and rapidly developed in the cloud but then moved in house for production use.

Rackspace Cloud Block Storage provides persistent block-level storage volumes for use with Rackspace next generation Cloud Servers. Volumes can be created and deleted independently of the Cloud Servers they are attached to. Rackspace Cloud Block Storage customers can create volumes ranging from 100 GB to 1 TB in size and choose from either SATA or SDD volume types. Cloud Block Storage provides persistent data storage for next generation Cloud Servers. Persistent storage can exist independent of your cloud server, even after the server has been deleted. The local storage bundled with Cloud Servers is ephemeral and exists only as long as the Cloud Server does. When the cloud server is deleted, so is its local storage. The minimum size for a Cloud Block Storage volume is 100 GB. The maximum volume size is 1TB. The default maximum capacity of Cloud Block Storage that can be consumed by a single customer account is 10TB

Table 2: Storage pricing for Rackspace

DISK	**Price/GB/Mo**
Standard	£0.09
SSD	£0.37

iii. Google Compute Engine

Google Compute Engine is a new service offering as of 2012 by Google which provides a Linux server and allows root access. It offers machines with up to 30GB memory and 8 CPU cores. This is an upgrade from their older service the Google Application Engine which only provided a limited Java environment. At the core of Google Compute Engine are virtual machine instances that run on Google's infrastructure. Each virtual machine instance is considered an

Instance resource and part of the Instance collection. When you create a virtual machine instance, you are creating an Instance resource that uses other resources, such as Disk resources, Network resources, Image resources, and so on. Each resource performs a different function. For example, a Disk resource functions as data storage for your virtual machine, similar to a physical hard drive, and a Network resource helps regulate traffic to and from your instances.

All resources belong to the global, regional, or zonal plane. For example, images are a global resource so they can be accessed from all other resources. Static IPs are a regional resource, and only resources that are part of the same region can use the static IPs in that region. If a zone is taken down for maintenance or suffers unexpected downtime, the offline zone is completely isolated from other zones and regions. Similarly, if a region falls offline, it is completely isolated from other regions. This allows you to design robust systems with resources spread across different control planes

Table 3: Storage allocation for Google computer

Storage Pricing per GB per month	
Standard Storage	Durable Reduced Availability Storage
$0.026	$0.02

iv. Windows Azure

With windows azure, the cloud storage is offered using the following two main strategies i.e. locally redundant storage and geographically redundant storage. The storage transactions in the form of read and writes were being charged at 0.01$ per 100000 transaction. The table below summarizes their allocation policy and pricing.

Table 4: Storage allocation policy for Windows Azure

Storage Offering	**Purpose**	**Maximum Size**
Local Storage	Per-instance temporary storage	250GB to 2TB

Windows Azure Storage	Variety of functions	N/A
Blob	Large binary objects such as video or audio	200GB or 1TB
Table	Structured data	100TB
Queue	Inter-process Messages	100TB
SQL Database	Relational Database Management System	150GB

STORAGE CAPACITY	**LOCALLY REDUNDANT**	**GEOGRAPHICALLY REDUNDANT**
First 1 TB [1] / Month	**$0.07** per GB	**$0.095** per GB
Next 49 TB / Month	**$0.065** per GB	**$0.08** per GB
Next 450 TB / Month	**$0.06** per GB	**$0.07** per GB
Next 500 TB / Month	**$0.055** per GB	**$0.065** per GB
Next 4000 TB / Month	**$0.045** per GB	**$0.06** per GB
Next 4000 TB / Month	**$0.037** per GB	**$0.055** per GB
over 9000 TB / Month	Customized pricing	Customized pricing

(http://www.windowsazure.com/en-us/pricing/details/storage/)

v. GO GRID

This cloud storage provider has two main strategies for allocating the storage resource. These include Block storage allocation and normal cloud storage. Block Storage is charged per gigabyte (GB) per month for the volume that is provisioned. There are no additional charges for I/O operations, or private network transfer, and charges are the same across data centers. The charges are at a flat rate of 0.12 dollars per month per gigabyte. Block Storage is built for speed and performance. Below are a few common use cases.

- **HighIOapps**
  Apps that require frequent interaction with raw, unformatted block-level storage and workloads, requiring frequent reads/writes and high IOPS.

- **Databases**
  Primary storage for a database, especially true when you want to cluster databases, which requires shared storage.

- **Exchange**
  Although Microsoft has made massive improvements to Exchange, the company still doesn’t support file-level or network-based (CIFS or NFS) storage, but only block-level storage.

- **NoSQLdatabases**
  Cassandra, MongoDB, or other NoSQL database storage; storage for relational databases, web caching, and indexing.

Normal cloud storage on the other hand involves Billing for Cloud Storage begins after the client exceeds the initial free 10 GB storage quota. Each additional stored GB is charged monthly according to the tiers below.

Table 5: Cloud storage policy for GOGRID

CLOUD STORAGE	PRICING
1-10 GB	Free
10 GB – 1 TB	$0.12 per GB
1 TB – 50 TB	$0.11 per GB
50 TB – 500 TB	$0.10 per GB
500 TB – 1,000 TB	$0.09 per GB
More than 1,000 TB	$0.08 per GB

(Source: http://www.gogrid.com/products/block-storage#use-cases)

Cloud providers in the Kenyan context

Safaricom Online Storage

This is done through the Web browser but will in the future be available in the form of a network drive. The Online storage via Atmos allows you to store and manage your data in a self-service and utility-like environment.

Features

- Online document editing
- Desktop application
- Easy search tool
- Access to your data anytime, anywhere
- Folder/directory upload
- Multi-user accounts
- Online collaboration
- Online sharing of large files
- Customized views

Benefits

- Single system – Efficiently store, manage, and aggregate distributed big data across locations through a single pane of glass. Gain a common view and central management.
- Seamless scalability – Add capacity, applications, locations or tenants to your Cloud with zero need to develop or reconfigure. Reduce administration time and ensure availability.

- Storage-as-a-Service – Allow enterprises and service providers to meter capacity, bandwidth, and usage across tenants. Enable users to self-manage and access storage.
- Easy storage access – Provide flexible access across networks and platforms for traditional applications, Web applications, Microsoft Windows, Linux, and mobile devices. Allow users and applications instant access to data.

Table 6: Packages and Pricing for storage for Safaricom Ltd.

Item	Details	Price Ex VAT	Price Inc VAT
Storage 100GB	100	KES 1,200	KES 1,392
Storage 200GB	200	KES 2,200	KES 2,552
Storage 400GB	400	KES 4,200	KES 4,872
Storage 500GB	500	KES 5,200	KES 6,032
Storage 800GB	800	KES 8,200	KES 9,512
Storage 1TB	1024	KES 10,440	KES 12,110
Storage 2TB	2048	KES 20,680	KES 23,989
Storage 5TB	5120	KES 51,400	KES 59,624
Storage 10TB	10240	KES 102,600	KES 119,016
Storage 20TB	20480	KES 205,000	KES 237,800

Safaricom Backup as a Service

The aim of the product it is to help Safaricom customers to avoid capital outlay for purchasing new backup equipment, ongoing media costs, staff costs, and running costs which are then limited to a monthly service fee. While traditional methods can be very effective, they are also capital and labour intensive. Safaricom Cloud Back-up Solution seeks to avoid these setbacks. Safaricom Cloud Backup setup and installation is a simple matter of downloading the software, and takes only a few minutes to set up. Data recovery is equally fast, as there is no searching for the right tape or waiting for IT staff to recover lost data. Once the application has been installed, data transfer will be performed via a secure Internet connection (SSL) from the client site to the Safaricom data store where the backup will reside.

Service Offers

- Disk-to-Disk data backup and recovery solution which is uniquely designed for network efficiency
- Centralized management.
- Policy-based control and ease of use.
- An effective and efficient platform for a totally automated and secure data backup and recovery for servers, databases, desktops and laptop devices.
- Eliminates risk of human error in the backup process.
- 2-Factor authentication to your secured data
- Backup disk capacity – scalable on demand

Features

- Faster backup and recovery - Data DE duplication significantly reduces backup windows by only storing unique daily changes while maintaining daily full backups for immediate single-step restore.
- Secure, off-site protection and enterprise class data encryption.
- Multiple agent deployment options include download, email and redistributable packages.
- Self-service recovery capabilities for employees.
- Powerful data history.

Benefits

- Flexible deployment - Avamar systems scale to 124 TB of DE duplicated capacity.
- It keeps data protected while in transit and at rest while also allowing it to be restored to any Internet-connected location.
- It makes the service easy to deploy to individuals - whether in the office or out of office.
- One-step recovery – every Avamar backup is a full backup, which makes it easy for you to browse, point, and click for a single-step recovery.
- Data is stored for the life of your contract unless it is deleted from your computer or replaced by a newer version – it will then be removed from your backup after 90 days.

Table 7: Packaging and Pricing for cloud backup service for safaricom Ltd.

Item	**Details**	**Price Ex VAT**	**Price Inc VAT**
Backup 20GB	20	KES 850	KES 986
Backup 40GB	40	KES 1,150	KES 1,334
Backup 50GB	50	KES 1,300	KES 1,508
Backup 100GB	100	KES 1,650	KES 1,914
Backup 200GB	200	KES 3,210	KES 3,724
Backup 400GB	400	KES 5,810	KES 6,740
Backup 500GB	500	KES 7,110	KES 8,248
Backup 800GB	800	KES 11,010	KES 12,772

Backup 1TB	1024	KES 13,922	KES 16,150
Backup 2TB	2048	KES 27,234	KES 31,591
Backup 5TB	5120	KES 67,170	KES 77,917
Backup 10TB	10240	KES 133,730	KES 155,127
Backup 15TB	15360	KES 200,290	KES 232,336
Backup 20TB	20480	KES 266,850	KES 309,546

2.3 Machine learning

2.3.1 Definition of machine learning?

Machine Learning is the study of computer algorithms that improve automatically through experience. Applications range from data mining programs that discover general rules in large data sets, to information filtering systems that automatically learn users' interests (mitchell,1996) .

Machine Learning is concerned with the design and development of algorithms that allow computers to evolve behaviors based on empirical data, such as from sensor data or databases. A major focus of Machine Learning research is to automatically learn to recognize complex patterns and make intelligent decisions based on data; the difficulty lies in the fact that the set of all possible behaviors given all possible inputs is too complex to describe generally in programming languages, so that in effect programs must automatically describe programs.

2.3.2 Applications of machine learning

In recent years many successful machine learning applications have been developed, ranging from data-mining programs that learn to detect fraudulent credit card transactions, to information-filtering systems that learn users' reading preferences, to autonomous vehicles that learn to drive on public highways. At the same time, there have been important advances in the theory and algorithms that form the foundations of this field.

The poor performance results produced by statistical estimation models have flooded the estimation area for over the last decade. Their inability to handle categorical data, cope with missing data points, spread of data points and most importantly lack of reasoning capabilities has triggered an increase in the number of studies using non-traditional methods like machine learning techniques (Yogesh Singh, et. al). The area of machine learning draws on concepts from diverse fields such as statistics, artificial intelligence, philosophy, information theory, biology, cognitive science, computational complexity and control theory.

2.3.3 Types of machine learning

There are two main types of Machine Learning algorithms. In this work, supervised learning is adopted here to build models from raw data and perform regression and classification.

- Supervised learning: Supervised Learning is a machine learning paradigm for acquiring the input-output relationship information of a system based on a given set of paired input-output training samples. As the output is regarded as the label of the input data or the supervision, an input-output training sample is also called labeled training data, or supervised data. Learning from Labeled Data, or Inductive Machine Learning (Kotsiantis, 2007). The goal of supervised learning is to build an artificial system that can learn the mapping between the input and the output, and can predict the output of the system given new inputs. If the output takes a finite set of discrete values that indicate the class labels of the input, the learned mapping leads to the classification of the input data. If the output takes continuous values, it leads to a regression of the input. It deduces a function from training data that maps inputs to the expected outcomes. The output of the function can be a predicted continuous value (called regression), or a predicted class label from a discrete set for the input object (called classification). The goal of the supervised learner is to predict the value of the function for any valid input object from a number of training examples. The most widely used classifiers are the Neural Network (Multilayer perceptron), Support Vector Machines, k-nearest neighbor algorithm, Regression Analysis, Artificial neural networks and time series analysis.

- Unsupervised learning: Unsupervised learning studies how systems can learn to represent particular input patterns in a way that reflects the statistical structure of the overall collection of input patterns. By contrast with supervised learning or reinforcement learning, there are no explicit target outputs or environmental evaluations associated with each input; rather the unsupervised learner brings to bear prior biases as to what aspects of the structure of the input should be captured in the output.

2.3.4 Techniques for supervised machine learning

In this section the researcher describes machine learning techniques, the ones that will be most relevant to our work.

***Linear Regression (LR) algorithm*:**

The goal of linear regression is to adjust the values of slope and intercept to find the line that best predicts Y from X. More precisely, the goal of regression is to minimize the sum of the squares of the vertical distances of the points from the line. When one thinks of regression , they think prediction. A regression uses the historical relationship between an independent and a dependent variable to predict the future values of the dependent variable. Businesses use regression to predict such things as future sales, stock prices, currency exchange rates, and productivity gains resulting from a training program. A regression models the past relationship between variables to predict their future behavior. To make better models, we minimize the errors .an error is considered to be the distance between the actual data and the model data. A Regression Line is drawn so that there is minimal amount of error in predictions for all of the already known values

Equation of a Regression Line

The equation of a straight line shown below may be viewed as one of the equations of a regression line

$F(x)=mx+b$

Variables, constants, and coefficients are represented in the equation of a line as

- x represents the independent variable

- $f\ (x)$ represents the dependent variable

-the constant b denotes the y-intercept and this will be the value of the dependent variable if the independent variable is equal to zero

-the coefficient *m* describes the movement in the dependent variable as a result of a given movement in the independent variable

A linear regression model fits a linear function to a set of data points. The form of the function is:

$$Y = \beta_0 + \beta_1 \cdot X_1 + \beta_2 \cdot X_2 + \cdots + \beta_n \cdot X_n$$

Where *Y* is the target variable, *X*1, *X*2,… *Xn* are the predictor variables, and , …, are coefficients that multiply the predictor variables is a constant (albers,suijis,2009)

***Artificial Neural Network (ANN)*:**

Neural networks in artificial intelligence are usually referred to as artificial neural networks (ANNs) and they are simple mathematical models defining a function f:x→y or a distribution over X or both X and y. The word network in ANN refers to the interconnections between the neurons in the different layers o each system. What attracts the most interest in neural networks is the possibility of learning. Given a specific task to solve, and a class function, learning means using a set of observations to find a function which solves the task in some optimal sense. This entails defining a cost function such that for the optimal solution, no solution has a cost less than the cost of the optimal solution. The cost function is an important concept of learning as it is a measure of how far away a particular solution is from an optimal solution to the problem solved. Learning algorithms search through the solution space to find a function that has the smallest possible cost. A Simple system may be considered to be comprised of three layers ,that is, the first layer which has input neurons which send data via synapses to the second layer of neutrons, and then via more synapses to the third layer of the output neutrons. More complex systems will have more layers of neutrons with some having more layers of input neutrons and output neutrons. An ANN is typically defined by three types of parameters as follows

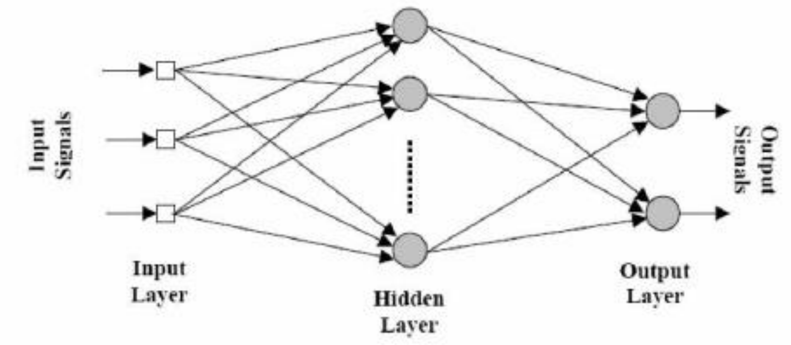
i. Interconnection pattern between the different layers of neurons

ii. The learning process for updating the weights of the interconnections

iii. The activation function that converts a neuron’s weighted input to its output activation

Training a neural network model essentially means selecting one model from the set of allowed models that minimizes the cost criterion. Most of the algorithms used in training artificial neural networks employ some form of gradient descent. This is done y simply taking the derivative of the cost function with respect to network parameters and then changing these parameters in a gradient-related direction.

It is defined by an interconnected group of functions that emulates a biological neural system and can collectively perform complex tasks. During the training phase, an ANN changes its structure based on external or internal information that flows through the network. *Radial Basis Function network* (RBFn) is a feed forward ANN, typically with three layers: input, hidden and output. A variable number of neurons form the key hidden layer, where Euclidean distance from the center of each neuron to the test case is computed and the RBF function applied. RBFn is very similar to k-nn, except for the fact that RBFn is a parametric method. The number of neurons in the hidden layer (number of neighbors in k-nn) affects the performance and the computational demands of RBFn. In the extreme case (over fitting), each data point can be the center of a neuron (single neighbor in k-nn). The use of RBFn combined with a Bayesian network was proposed for eliminating attributes with low correlation with the outcome (Duan&nadem, 2009).



Input Layer

A vector of predictor variable values (*x*1…*xp*) is presented to the input layer. The input layer (or processing before the input layer) standardizes these values so that the range of each variable is -1 to 1. The input layer distributes the values to each of the neurons in the hidden layer. In addition to the predictor variables, there is a constant input of 1.0, called the *bias* that is fed to each of the hidden layers; the bias is multiplied by a weight and added to the sum going into the neuron.

Hidden Layer

Arriving at a neuron in the hidden layer, the value from each input neuron is multiplied by a weight (*wji*), and the resulting weighted values are added together producing a combined value *uj*. The weighted sum (*uj*) is fed into a transfer function, σ, which outputs a value *hj*. The outputs from the hidden layer are distributed to the output layer.

Output Layer

Arriving at a neuron in the output layer, the value from each hidden layer neuron is multiplied by a weight (*wkj*), and the resulting weighted values are added together producing a combined value *vj*. The weighted sum (*vj*) is fed into a transfer function, σ, which outputs a value *yk*. The *y* values are the outputs of the network.

If a regression analysis is being performed with a continuous target variable, then there is a single neuron in the output layer, and it generates a single *y* value. For classification problems with categorical target variables, there are *N* neurons in the output layer producing *N* values, one for each of the *N* categories of the target variable.

The goal of the training process is to find the set of weight values that will cause the output from the neural network to match the actual target values as closely as possible. There are several issues involved in designing and training a multilayer perceptron network:

i. Selecting how many hidden layers to use in the network.
ii. Deciding how many neurons to use in each hidden layer.
iii. Finding a globally optimal solution that avoids local minima.
iv. Converging to an optimal solution in a reasonable period of time.
v. Validating the neural network to test for over fitting.

***Support Vector Machine (SVM) algorithm*:**

It is a kernel method for solving classification problems (vapnik, et.al) and regression problems especially for scenarios with non-linear learning pattern. The attribute space is transformed by the kernel function into possibly a high-dimension feature space where an optimal linear hyperplane is found by maximizing the margin between the so called support vectors. The advantages of this method include the limited number of parameters to choose, and the ability to handle large numbers of attributes and non-linear scenarios without local minima problems. A comparison of radial basis function neural networks with SVM has been presented with lower errors for SVM in some scenarios at the cost of higher computational demand.

***Time series analysis*:**

Time series analysis is the process of using statistical techniques to model and explain a time-dependent series of data points. Time series forecasting is the process of using a model to generate predictions or forecasts for future events based on known past events. Time series data has a natural temporal ordering and this differs from typical data mining/machine learning applications where each data point is an independent example of the concept to be learned, and the ordering of data points within a data set does not matter. Time series are analyzed in order to understand the underlying structure and function that produce the observations. Understanding the mechanisms of a time series allows a mathematical model to be developed that explains the data in such a way that prediction, monitoring, or control can occur.

It is assumed that a time series data set has at least one systematic pattern. The most common patterns are trends and seasonality. Trends are generally linear or quadratic. To find trends, moving averages or regression analysis is often used. Seasonality is a trend that repeats itself systematically over time. A second assumption is that the data exhibits enough of a random process so that it is hard to identify the systematic patterns within the data. Time series analysis techniques often employ some type of filter to the data in order to dampen the error. Other potential patterns have to do with lingering effects of earlier observations or earlier random errors.

General model of time series

Let an observed discrete time series be $s_1, \ldots , s_T$. This means that we have T numbers which are observations on some variable made at T equally distant time points, which we may label 1, 2, . . . , T.A fairly general model for the time series can be written

$s_t = g(t) + \phi_t$ where $t = 1, \ldots , T$

The observed series is made of two components

Systematic part: g(t), also called *signal* or *trend*, which is a deterministic function of time

Stochastic sequence: a residual term ϕ_t, also called *noise*, which follows a probability law.

(Mitchell, 1996)

2.3.5 Application of supervised machine learning techniques in resource management

Machine learning theory presents various theoretical ideas on improving learning while the practical aspect involves construction and improvements of algorithms for implementing the learning. There is much literature available on machine learning and their areas of applications.

The use of Machine learning algorithms to predict application resource consumption is an appealing approach that has been pursued by several previous studies (matsunaga& fortes, 2010).

The prediction of resources such as amounts of CPU, memory, disk and network required by an application and the length of time which the resources are occupied can be viewed as a supervised machine learning problem (matsunaga& fortes,2010).The system needs to learn a concept based on a collection of historical data of n previous runs of the application. Each previous observation is observed as training data. Examples of machine learning algorithms used in learning and prediction of resource usage and consumption include linear regression algorithm(LR),Artificial neural networks (ANN),support vector machines(SVM),and Time series methods (matsunaga& fortes,2010).

Profile-Driven Storage provides visibility into an organization’s storage pool, letting it optimize and automate storage provisioning. It gives administrators the ability to overcome upfront storage provisioning challenges, such as capacity planning, differentiated service levels and managing capacity headroom. Administrators can meet growing business needs by provisioning data stores at scale, eliminating the need to provision virtual machines on a case-by-case basis.

- Manage initial and ongoing virtual machine placement based on pre-defined requirements.
- Create data store clusters to support Storage DRS.
- Gain deep insight into storage characteristics via integration with vSphere APIs for Storage Awareness (VASA).

Dynamic Storage Provisioning

Using Profile-Driven Storage, various storage characteristics, including SLA, availability and performance, can be requested in a virtual machine storage profile. These profiles are used to ensure that only those data stores or data store clusters that are compliant with the virtual machine storage profile are made available. The virtual machine storage profile can also help select a similar type of data store when creating a Storage DRS data store cluster. Profile-Driven Storage will reduce manual administration for virtual machine placement while improving virtual machine SLA storage compliance

(http://www.vmware.com/products/vsphere/features/profile-driven-storage.html)

Accurate modeling of an application’s performance is very useful both for users and cloud service providers. However, the non-linear relationship of resource allocations to application performance, the interplay of resource usage across different types of resources, and resource contention in a virtualized environment makes it very difficult to create application performance models. The researchers identified three VM resource control parameters as sufficient inputs for creating performance models. They also evaluated the effectiveness of artificial neural network (ANN) and Support Vector Machine (SVM) techniques for modeling and demonstrated that these are superior to conventional regression-based approaches. In order to further increase the accuracy of these techniques, the researcher presented a sub-modeling technique that substantially reduced prediction errors across five virtualized benchmark workloads from the

RUBiS and Filebench suites. Median and 90th percentile prediction errors using ANNs were reduced from 7.14% and 101.68% respectively (averaged across the workloads) for a correctly configured single global model to 4.36% and 29.17% with sub-modeling. Finally, when the models were used in VM sizing experiments, they delivered optimal results for 65% of the sizing problems we studied and produced sizes that were close to optimal for the remaining 35%. They expect that cloud users and service providers can benefit from the ability to create accurate performance models for their virtualized workloads and utilize such models for accurate VM sizing and placement (sajib kundu et. al).

Another study on the use machine learning techniques to map out resource consumption was done by adrea matsunanga and jose fortes.The researcher reported in the paper considered the problem of accurately predicting application resource usage, reviewed and discussed several noteworthy machine learning algorithms considered by previous work, proposed and implemented PQR2, an extension of an existing classification tree algorithm, and compared all solutions (including the new PQR2 algorithm) under several conditions. Experiments predicting execution time, memory and disk requirements for two popular bioinformatics applications, BLAST and RAxML, were performed on a heterogeneous environment. Overall, PQR2 exhibited better accuracy when compared to other algorithms, due to its ability to better adapt to scenarios with different characteristics (linear and non-linear relationships, high and low density of training data points) by choosing different models for its nodes and leaves. At a more general level, the two main conclusions from the work reported in this paper are as follows:

The scenarios requiring application resource prediction present a diverse behavior, making different algorithms perform better in different situations. The use of methods that can adapt to these situations by considering different configurations and algorithms is key for improving the quality of the prediction without requiring manual tuning. The resulting algorithms may be computationally more demanding during training, but this is usually not a concern as there is no need to generate a new model very often. Roughly, using the largest dataset (BLAST), PQR2 required a few minutes to create the model and a few milliseconds to produce a single prediction, indicating practicality of PQR2 for production deployments. PQR2 proved to be the best solution for BLAST and RAxML and should be considered as candidate solution for other applications.

Attributes can have high impact on the performance of the learning algorithms. The use of system performance attributes showed to be relevant for execution time prediction whereas application specific attributes were pertinent for all scenarios. This work makes the case for including as many attributes as available, while letting the algorithms analyze the relevance of the attributes when necessary. For cloud and grid computing scenarios, where resources are outsourced, the provision of this information to its users (or services acting on behalf of the users) through the use of benchmarks and runtime monitoring, especially of shared resources, can bring several benefits. Although this information is not readily available on a per application run basis, especially for shared resources, we expect it to become available in the near future (Amazon CloudWatch is one such example limited to a virtual machine instance). Improved prediction can result in better system utilization can avoid application abortion in system that enforce accurate resource reservation, as well as significant savings when choosing the appropriate pay- as-you-go resource (matsunaga& fortes,2010).

2.3.6 Tools used in machine learning and predictive modeling

Machine learning tools are utilities which can be used to analyze statistical datasets to automatically learn users' interests. One of the most useful applications of statistical analysis is the development of a model to represent and explain the relationship between data items (variables).These tools comprise of a collection of various algorithms that are useful in machine learning, and they allow users to capture datasets then they analyze these datasets for relationships based on these algorithms. These machine learning tools also have a graphical output representation utility which displays the results of the learning in the form of graphical charts and tables. Some of these tools include:

Sysweka model

Machine Learning techniques based on Weka are adopted to build a middleware platform called "SysWeka". Weka (Waikato Environment for Knowledge Analysis) is a popular suite of machine learning software written in Java, developed at the University of Waikato, New Zealand.Sysweka extends Weka capabilities and provide a software interface for usage by higher application for managing resources on cloud systems(Alonso et.al).Weka supports several standard data mining tasks, more specifically, data preprocessing, clustering, classification, regression, visualization, and feature selection. All of Weka's techniques are predicated on the assumption that the data is available as a single flat file or relation, where each data point is described by a fixed number of attributes (normally, numeric or nominal attributes, but some other attribute types are also supported). Weka provides access to SQL databases using Java Database Connectivity and can process the result returned by a database query. It is not capable of multi-relational data mining, but there is separate software for converting a collection of linked database tables into a single table that is suitable for processing using Weka. Another important area that is currently not covered by the algorithms included in the Weka distribution is sequence modeling (Ian H. Wittenet. al, 2011).

DTREG

DTREG is one of the most useful applications of statistical analysis in the development of a model to represent and explain the relationship between data items (variables). Many types of models have been developed, including linear and nonlinear regression (function fitting), discriminant analysis, logistic regression, support vector machines, neural networks and decision trees (Phillip H. Sherrod, 2009).

Each method has its advantages. There is no single modeling method that is best for all applications. DTREG provides the best, state-of-the-art modeling methods including neural networks, decision trees, TreeBoost, decision tree forests, support vector machines (SVM), gene expression programming, K-Means clustering, discriminant analysis and logistic regression. By applying the right method to the problem, the analyst using DTREG should be able to match or exceed the predictive ability of any other modeling program DTREG is a Predictive Modeling Software that builds classification and regression decision trees, neural networks, support vector machine (SVM), GMDH polynomial networks, gene expression programs, K-Means clustering, discriminant analysis and logistic regression models that describe data relationships and can be used to predict values for future observations.

DTREG accepts a dataset containing of number of rows with a column for each variable. One of the variables is the “target variable” whose value is to be modeled and predicted as a function of the “predictor variables”. The tabular dataset in the form of rows and columns is the only format that DTREG accepts data in.

DTREG analyzes the data and generates a model showing how best to predict the values of the target variable based on values of the predictor variables using a number of tests for accuracy from the various predictions. DTREG can create classical, single-tree models and also TreeBoost and Decision Tree Forest models consisting of ensembles of many trees. DTREG also can generate Neural Networks, Support Vector Machine (SVM), Gene Expression Programming/Symbolic Regression, K-Means clustering, GMDH polynomial networks, and Discriminate Analysis, Linear Regression, and Logistic Regression models.

Rapid miner

RapidMiner is a software platform developed by the company of the same name that provides an integrated environment for machine learning, data mining, text mining, predictive analytics and business analytics. It is used for business and industrial applications as well as for research, education, training, rapid prototyping, and application development and supports all steps of the data mining process including results visualization, validation and optimization This is an environment for machine learning, data mining, text mining, predictive analytics, and business analytics. It is used for research, education, training, rapid prototyping, application development, and industrial applications. RapidMiner provides data mining and machine learning procedures including: data loading and transformation (ETL), data preprocessing and visualization, modeling, evaluation, and deployment (Rapidminer).

2.5 summary of literature review

As per the literature study, the researcher was able to review cloud platforms and the various machine learning approaches under supervised learning and how they could be used to predict resource consumption. More research was evidently needed on issues relating to learning customer usage patterns for the case of storage resources most of them being statistical techniques as suggested by literature reviewed concerning the IaaS cloud computing providers and more specifically Safaricom limited. Various tools also exist for the management of the cloud computing IaaS storage resources and each one of them is applicable for some specific user needs.

2.6 Conceptual model

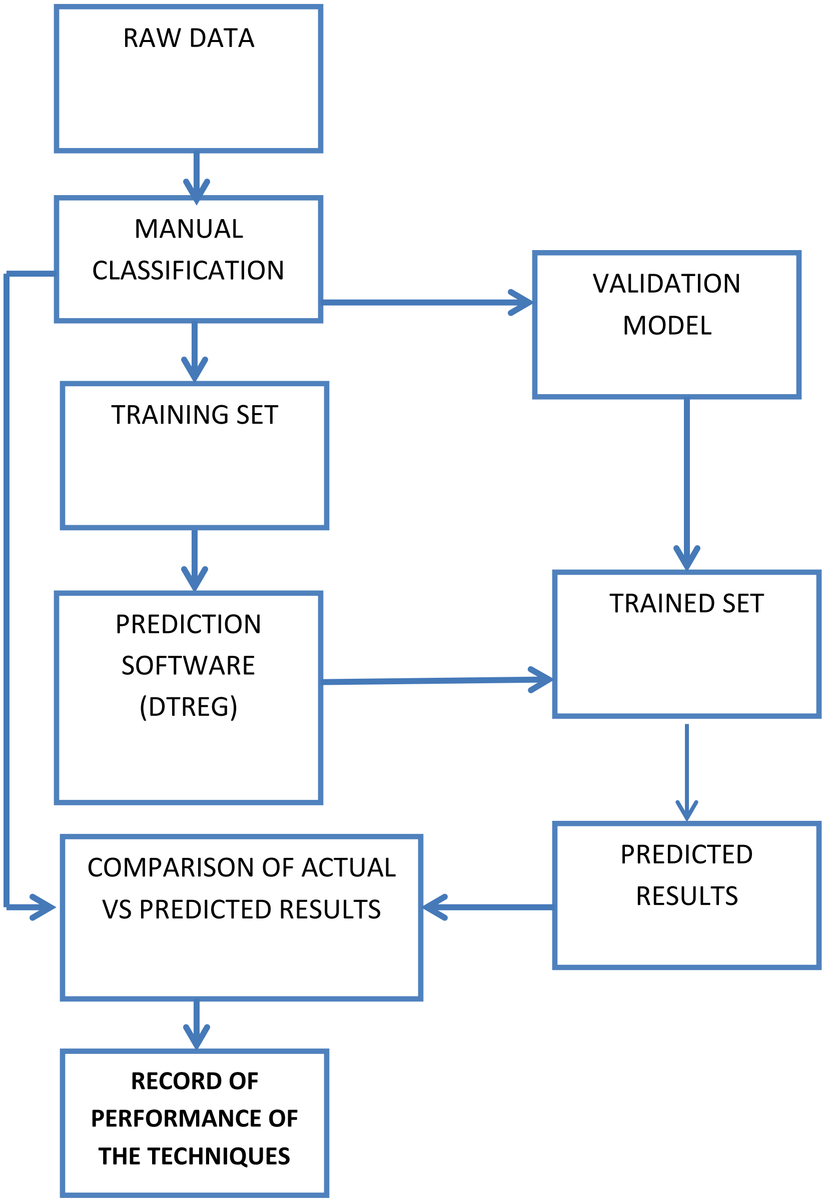

RAW DATA
MANUAL CLASSIFICATION
VALIDATION MODEL
TRAINING SET
TRAINED SET
PREDICTION SOFTWARE (DTREG)
COMPARISON OF ACTUAL VS PREDICTED RESULTS
PREDICTED RESULTS
RECORD OF PERFORMANCE OF THE TECHNIQUES

Figure 2-Process for using a machine learning technique to predict client storage resource usage.

CHAPTER THREE : METHODOLOGY

3.0 Introduction

Research methodology is a way to systematically solve the research problem. It may be understood as a science of studying how research is done scientifically. In it we study the various steps that are generally adopted by a researcher in studying his research problem along with the logic behind them. It is necessary for the researcher to know not only the research methods/techniques but also the methodology (Kothari, 2004).The objective of the research was to carry out a comparative study of three machine learning techniques to identify which one could best be used for learning of storage resource usage patterns for cloud clients and giving predictions of future resource usage patterns. In this case, the researcher focused on supervised learning because, from the data collected which could be used as training data for the learning and prediction through the use of the machine learning techniques.

3.1 Research design

3.1.1 Introduction

This is a detailed outline of how the research was designed. A research design will typically include selection and operationalisation of variables, selection of the type of study, selection of data collection instruments, selection of the research sampling technique and data analysis the intended means for analyzing data collected.

3.1.2 Selection of variables/Type of data required

Dependent variable: A dependent variable is one whose values are to be modeled and predicted by other variables. The dependent variables or target variables in this study were usage of the storage resource on a monthly basis, and the total amount of resource consumed after six months.

Independent variables: An independent variable also known as predictor variable is one whose value will be used to predict the value of the dependent or target variables.

The independent variables in this study are the client requests for resources, and number of users in the organization while the dependent variable was the resource usage after a period of six months, number of users in the organization and the type of cloud IaaS storage service the client is offered.

3.1.3 Type of study

In this case the researcher used the research approach is experimental research. The experimental research design has the following generals steps.

i. Identify and define the problem
ii. Formulate hypothesis and deduce its consequences
iii. Construct an experiment that represents all the elements conditions and relations
iv. Conduct experiments
v. Compile the raw data and analyze it
vi. Conclusion

The research methodology used was experimental research which involved the use of the framework for ensemble learning (ELF) (Hsuan-Tien lin, ling li, 2008) .It is a stand-alone supervised machine learning framework. ELF is able to solve regression as well as classification problems. The optimization target can be the RMSE, MAE, AUC or the classification error. The ELF supports multi-class classification problems and multi-domain classification. Multi-domain means that we have more than one label per example. The ELF has well implemented base learners. The ensemble functionality of the framework is realized with stacking, cascade learning and residual training. Stacking is a simple linear combination. ELF has the opportunity of cascade learning, which is an extension of the features with predictions from other models. Parameter selection can be done with cross-validation or bagging. Parameter selection means searching for good meta-parameters in order to control over fitting of each individual model.

i. Data collection
ii. Analysis and preparation of data
iii. Run data through machine learning tool
iv. Test various prediction models using machine learning tools

v. Repeat prediction accuracy experiments with various models
vi. Analysis of results

3.1.5 Data Collection of training data

3.1.5.1 Data collection instruments

The data was collected through the use of questionnaires which were presented to the Safaricom systems engineers. A sample of this has been attached in the appendix section (appendix 3) of this document. Also through secondary sources which includes document review for the client request

3.1.5.2 Research Sample design

3.1.5.2.1 Research population

The resource consumption data was collected from Safaricom limited while 70 % of the data was simulated using curve fitting. Safaricom live data about how clients are using the requested storage resource was collected for the purpose of the research study. This included data about storage resource allocation, resource utilization, and the client request for these resources. The data was on nature of organization (size and magnitude), resource requests storage, and resource usage for storage. This data was for corporate organizations.

The data collected to be collected was for the cloud storage resource requests and usage for the clients of Safaricom ltd. These were the two most relevant data items as pertains to the research experiments that were to be done. The data was collected through face to face interviews with the Safaricom engineers responsible for cloud computing services at Safaricom. The data collected was for duration of six months. This was the period from January 2013 up to and including June 2013.The data included those requests ranging between 1000 gigabytes to 10000 gigabytes. The rest of the data to be used for the experiments would be simulated.

Simulation of additional dataset

Out of the two hundred records in our dataset that were used for the research, 30 data elements were live data from Safaricom while the other 170 was generated through simulation. This data has been attached in the appendix section on sample data experimented on, of this document where the first thirty records represent the live data collected while the remaining one seventy records were simulated. The justification for the simulation is because, for the learning algorithm work sufficiently, it requires more training data set where 200 records would prove sufficient.

Curve fitting software (statfit)

The statfit software was used to simulate part of the data that was used for the study. It works by identifying the curve of best fit for the data and that we can use this curve to generate more data.

Through the use of the tool **statfit**, the live data which was collected from Safaricom was fed into the statfit software and through tests for goodness of fit, the software was able to curve fit the data into a lognormal type of distribution and output for us the various parameters of this distribution including the ***minimum value***, the ***mean*** of included normal and the ***standard deviation*** of included normal which are key parameters when using lognormal distributions. For the case of the data that the researcher used, the equations generated by the tool for resource requests was lognormal in nature and it had the following parameters ***lognormal (1000, 8.1, 0.619)*** and the equation for resource usage was also lognormal and it had the following parameters ***lognormal (0,7.01,0.738).***We could then use this parameters to generate more data using the “generate” option within the statfit tool. The researcher varied the parameters of the lognormal equation including the minimum value of data which could be requested so as to generate more values since the simulation tool could only generate data in batches of fifty elements. A total of 250 data elements were used where 30 were live data collected from Safaricom while 220 were the simulated data items A sample of this dataset can be found in the appendix of this document.

3.1.7 Preparation of the data for training

Classification of data

Once the data was collected, it was then classified based on magnitude of client requests for the cloud computing storage service on a six month cumulative basis measured in gigabytes. The reason for the classification was to group the various clients' requests so as to identify those whose requests are above 1000 GB. The classification index for both the dependent and independent variables is given by the table below.

Classification index

Table 8-classification of client requests for storage on a six month cumulative basis

LABEL	INDEX
VERY HIGH	5
HIGH	4
MEDIUM	3
LOW	2
VERY LOW	1

Table 9-classification of cloud storage service request in Gigabytes

CLOUD SERVICE REQUESTS in Gbs(cr)	CLASSIFICATION
1000-2000	1
2001-4000	2
4001-6000	3
6001-8000	4
ABOVE 8000	5

Training Data

The training data was comprised of 200 data elements and it was presented in Microsoft excel's .csv format. It was made up of parameters which included, the amount of storage requested, amount of storage used and the number of users within a particular organization. This was the data which was used for experimentation

3.1.7 Prediction accuracy experiments

Experiments were done on the data which was to represent cloud client service requests and the actual usage of these services requested. This data was run on the DTREG software and two main files were generated that is, training data and validation data. The two files had several rows representing the various clients and two columns, one for requested resource and the other for actual usage.

Two sets of data were used in the study. Training data set used for the analysis and the validation data set used for validation. The training dataset has been attached in the appendix section while the validation dataset is generated by the learning tool DTREG.

3.1.7.1 Experimental testbed for Prediction accuracy

The experiment was done using software called DTREG that would take in .csv files representing the training set and the testing data, train the classifier using the training files and then use the test file to perform the classification task on the test data. DTREG would then make modifications to the data according to the model chosen and then when the analysis is run, it produces results.

The experiments were performed using the following software's:

Simulation software

The simulation software used was DTREG version 10.7.8

Operating system

The experiments were done on Microsoft windows 7 service operating system.

Spreadsheets (MS excel)

Microsoft was used for data analysis and result analysis to generate the bar graphs and line graphs.

The training experiments to be carried out using DTREG. DTREG includes a full Data Transformation Language (DTL) for transforming variables, creating new variables and selecting which rows to analyze.

3.1.7.2 Prediction procedure

How to run data through DTREG: DTREG prediction software was given the data set for the cloud computing service requests and it divided the data into the two data sets. The following are fundamental steps that were undertaken

i. Load training file
ii. Load prediction file
iii. Assign class (predicted attribute)
iv. Select a prediction tool
v. Perform classifications training /testing using training/testing files
vi. Evaluate classification using cross validation method
vii. Perform predictions using prediction file
viii. Save predictions output as predictions file

Experiment design

The classified data, which is, resource request and utilization data was then subjected to experimentation. The experiments were the test for accuracy done using the following measures: Root mean square error, mean absolute percentage error and mean square error .They included subjecting the training data to the DTREG tool getting the predictions and evaluating the accuracy of prediction. The significance of this data is for training examples which will be run on the machine learning tool (DTREG).From the data we can be able to survey for suggested trends and patterns on the requests versus usage.

Machine learning methods were experimented upon in order to find the best predicting tool that is accurate for the case of a cloud computing environment. The following machine learning methods were used in the study: linear regression, Support Vector Machine (SVM) and artificial neural networks (ANNs)

Various types of experiments were carried out and this included Test for accuracy in the actual verses predicted results. Experiments were done on the data which was to represent cloud client service requests and the actual usage of these services requested. This data was run on the DTREG software and two main files were generated that is, training data and validation data.

The two files had several rows representing the various clients and two columns, one for requested resource and the other for actual usage. The experiments for accuracy described earlier were done using software called DTREG that would take in .csv files representing the training set and the testing data train the classifier using the training files and then use the test file to perform the classification task on the test data. DTREG would then make modifications to the data according to the model chosen and then when the analysis is run, it produces results.

3.1.8 Data Analysis

3.1.8.1 Processing of prediction accuracy data

Tabulation of the prediction accuracy data collected

The data to be collected from the experiments included the prediction results from the various machine learning techniques in the form of graphs and tables comparing the actual verses the predicted results, the coefficient of variance between the actual verses the predicted results and the various measures of accuracy for the various machine learning techniques including mean absolute percentage error (MAPE), correlation between actual and predicted variables, mean square error (MSE).

The experiments were done using DTREG software and the results tabulated and also presented in form of graphs generated from Microsoft Excel.

The Actual data that was provided to the Model was compared with the predicted results generated by the model using graphs.

3.1.8.1 Comparison of the Machine learning techniques

The machine learning algorithms were compared included Support vector machine algorithm (SVM), linear regression and artificial neural networks (ANN).The experiments were run on DTREG while changing the various parameters so as to see how the results differ. The experiments involved a test for accuracy in the prediction of a machine learning algorithm. The measures observed in the analysis included the coefficients of variance (CV) in the learning algorithms, mean absolute percentage error (MAPE), correlation between actual and predicted variables, mean square error (MSE).

As part of the experiments, the following metrics will be evaluated so as to measure the algorithms' performance. This metrics include mean absolute percentage error (MAPE), Coefficient of Variation, root mean square error (RMSE), Correlation between actual and predicted data

CHAPTER FOUR : RESULTS ANALYSIS AND EVALUATION

4.0 Introduction

This section describes the review and analysis of the results which were collected after conducting the various comparisons of the machine learning algorithms using the DTREG tool. It also contains the various results that were used to measure the accuracy of the various algorithms used.

4.1 Data sets collected

The data set collected comprised of 30 records from Safaricom which were used to simulate another 200 datasets as the training dataset. The training data was comprised of 200 data elements and it was presented in Microsoft excel's .csv format. It was made up of parameters which included, the amount of storage requested, amount of storage used and the number of users within a particular organization. This was the data which was used for experimentation.

4.1.1 Data set collected in tabular format

The data which was collected from Safaricom was used to generate some other data through simulation and these datasets have been attached in the appendix section of this document

4.1.2 Graphical representation of data for Client resource(Storage) usage over six months

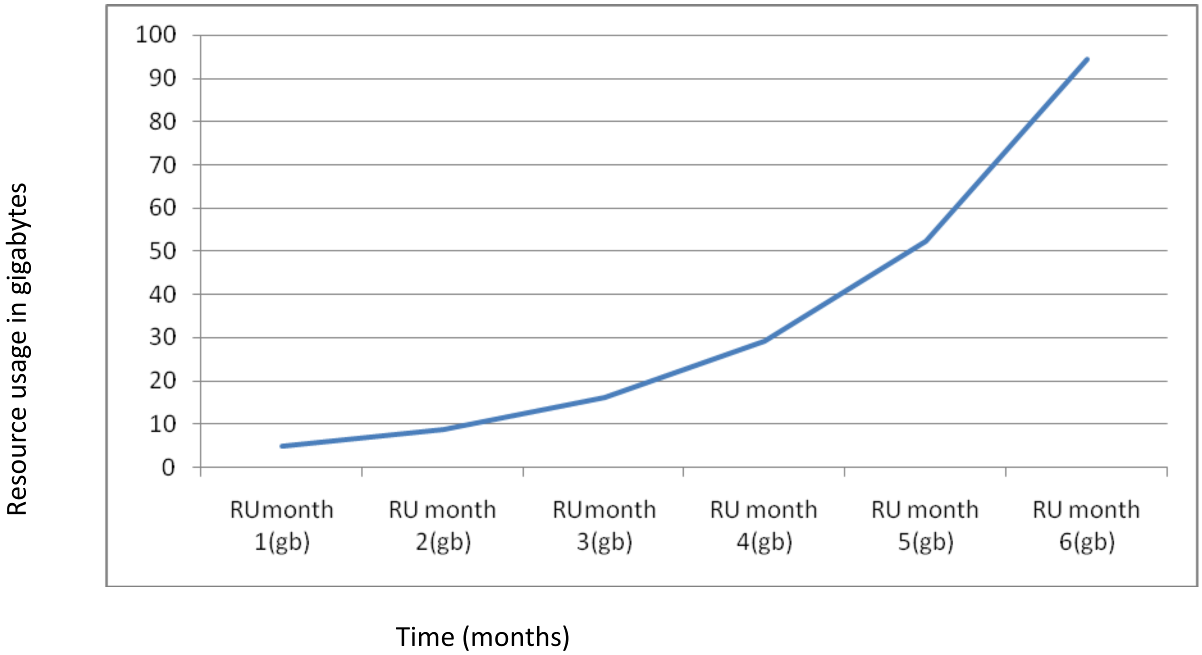


Figure 3-Request verses usage over six months

This graph enables us to identify the trend that client usage for the requested resource is not stagnant and it keeps on increasing steadily with time.

4.1.3 Resource requests verses the usage

This was done using Microsoft excel and the line graph below gives a representation of the requests. The analysis from this is that the users tend to request for much more storage resource than they actually use.

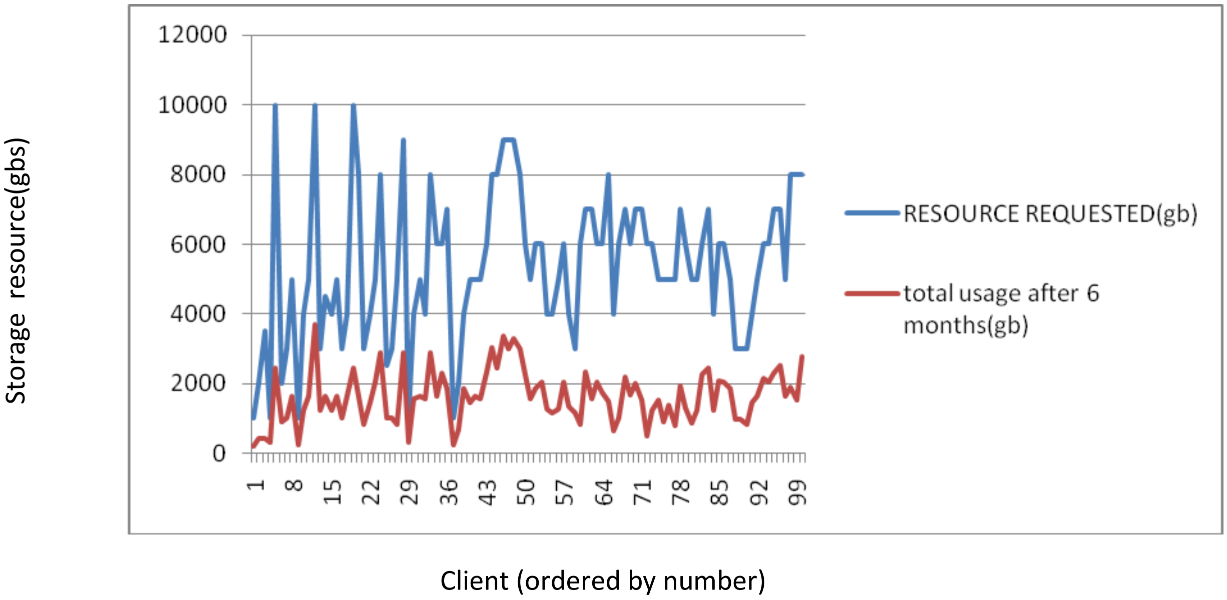


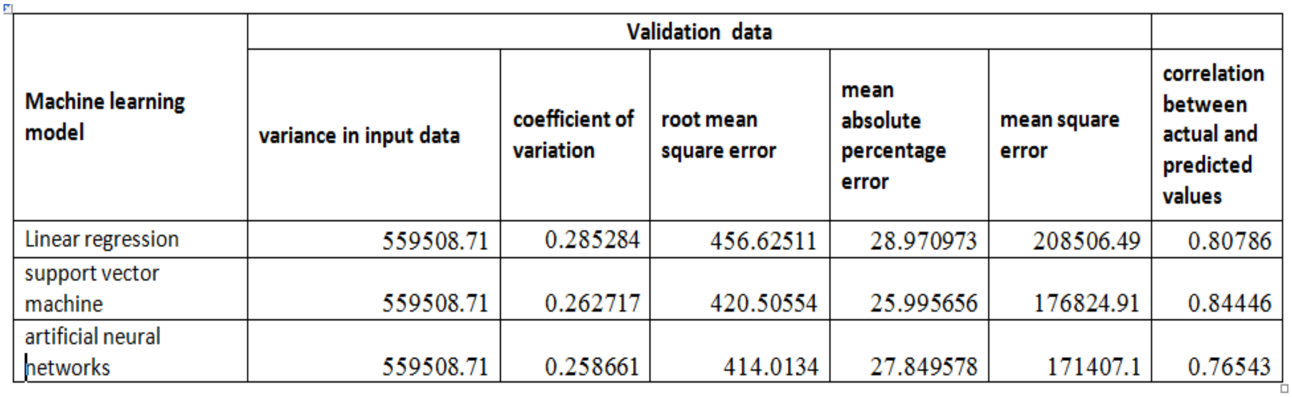
Figure 4: Resource requested versus usage

4.2 Results of accuracy of prediction of resource usage

4.2.1 Tabular presentation

The results obtained from the Machine learning tool were printed out in the form of reports from the software

Table 10-measures of accuracy for various learning model



Machine learning model	Validation data					
	variance in input data	coefficient of variation	root mean square error	mean absolute percentage error	mean square error	correlation between actual and predicted values
Linear regression	559508.71	0.285284	456.62511	28.970973	208506.49	0.80786
support vector machine	559508.71	0.262717	420.50554	25.995656	176824.91	0.84446
artificial neural networks	559508.71	0.258661	414.0134	27.849578	171407.1	0.76543

4.2.2 Graphical presentation of results

4.2.2.1 Coefficient of variation

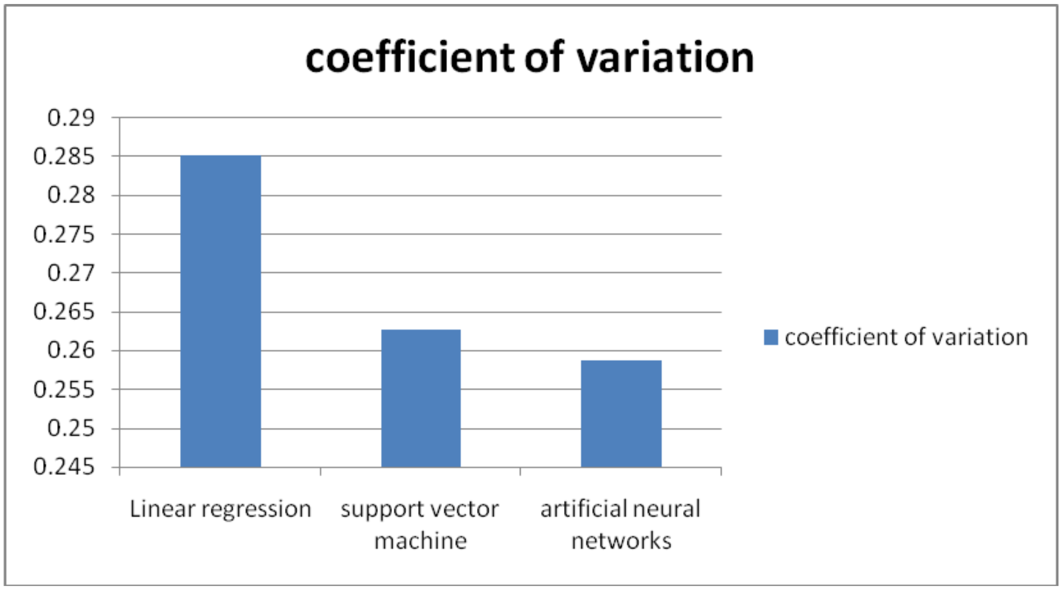


Figure 5: Coefficient of variation

4.2.2.2 Root mean square error

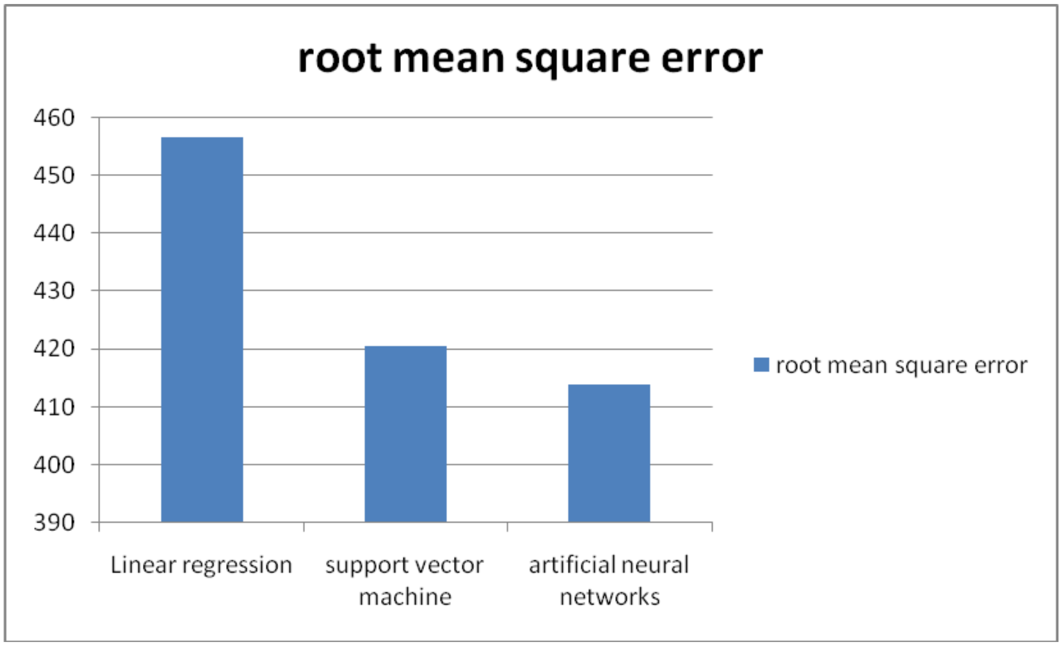


Figure 6: Root mean square error

4.2.3.3 Mean absolute percentage error

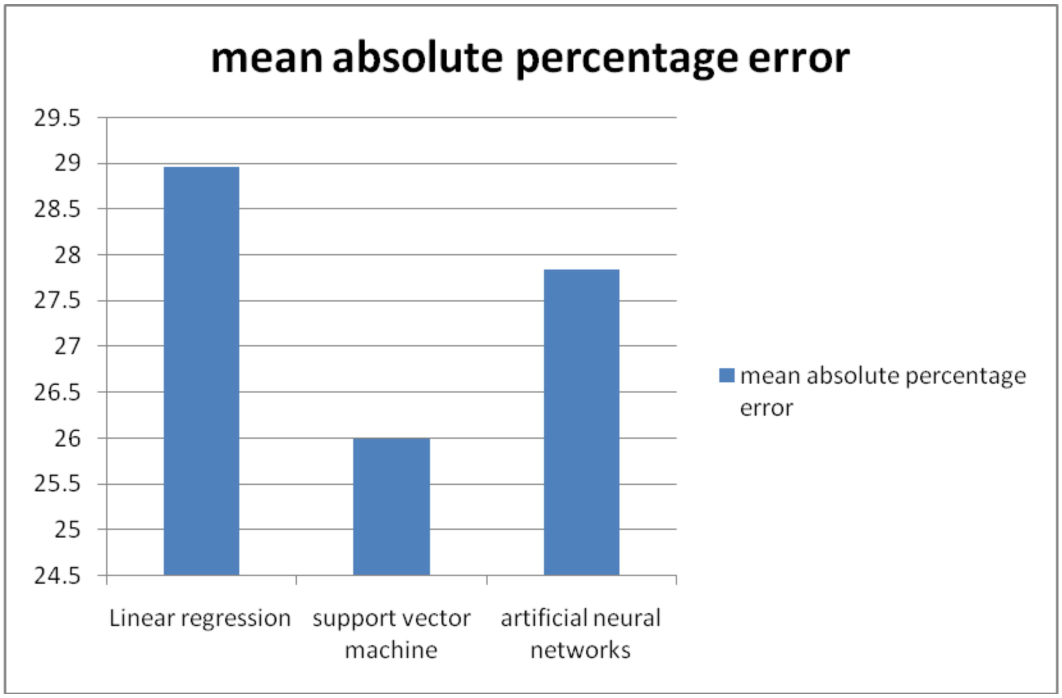


Figure 7: Mean percentage error

4.2.2.4 Correlation between actual and predicted data

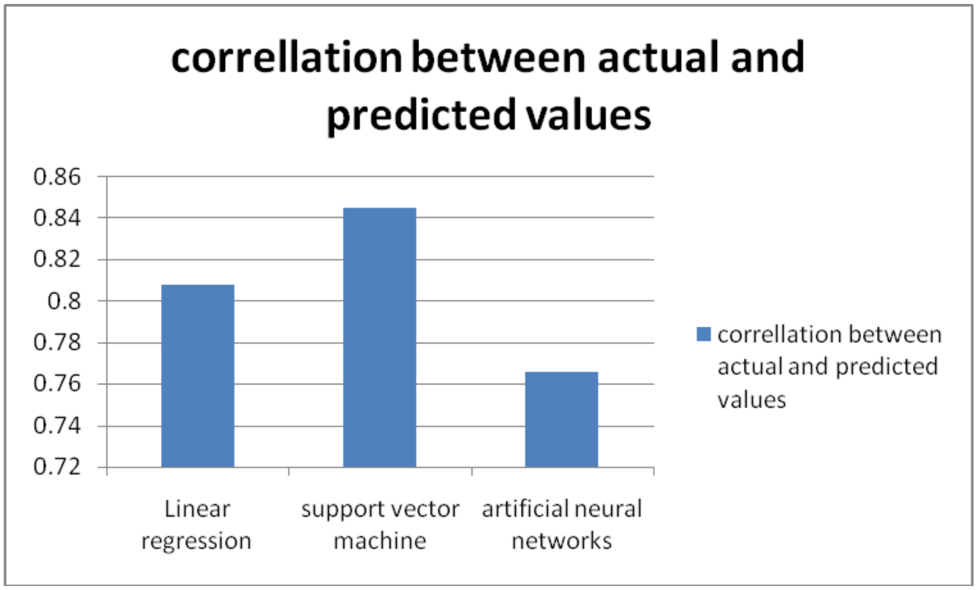


Figure 8: Correlation between actual and predicted values

4.3 Comparison of accuracy of the predictions by the various algorithms

- The lower the Coefficient of Variation, the smaller the residuals relative to the predicted value. This is suggestive of a good model fit. As from the analysis and this case ANN has the best model fit followed by SVM since they exhibit the lower coefficients of variation.
- Two or more statistical models may be compared using their MSEs as a measure of how well they explain a given set of observations: The unbiased model with the smallest MSE is generally interpreted as best explaining the variability in the observations. From the analysis of our experimental results and according to our dataset, ANN and SVM had the smaller values hence they would be the preferred choice of algorithm.
- When considering this metric the smaller the mean absolute percentage error (MAPE) the better and from the analysis of our experimental results data SVM had theleast mean percentage error.
- From the graph, SVM had the most corellation between the actual and predicted values.The higher the correllation the better for a prediction model.From the analysis of the experimental results SVM would be the best machine learning technique judging by the metric of correllation.
- The researcher then usede the average of the above measures stated toevauate which will be the best machine learning algorithm to use for this case of cloud storage resource usage.All the three measures that is root mean square error,mean absolute deviation and the correllation between actual and predicted data.

From the analysis of the results of experiments' carried out by the researcher of the various metrics mentioned earlier, that is, MAPE, RMSE, coefficient of variation and comparison between actual verses predicted data, it is evident that support vector machine (SVM) is the best machine learning approach for this particular case and it can be used as a tool for prediction of client storage resource usage patterns for the case of cloud computing IaaS.

Support Vector Machines algorithm can therefore be used as a tool where the storage resource usage patterns can be surveyed and then the trend that is observed be use to advice clients on their future storage resource requirements. The observed usage patterns can also be used by cloud computing providers when budgeting for their resource since they can be able to get the projected clients storage resource requirements and therefore better future planning on their part regarding the resources.

4.4 Limitations and challenges

The researcher acknowledges the challenge in compiling the actual usage data from the cloud service provider .For this reason the researcher used estimates for the raw data and assumed that the customer resource request and usage patterns remain fairly constant.

Due to time constraints, the researcher used only DTREG as his evaluation tool therefore the researcher advices that other tools may be used to make the study more comprehensive.

CHAPTER FIVE : CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

In the study conducted for the purpose of this thesis, the main objective was to conduct a comparative study of the machine learning techniques for optimizing the provision of storage computing in cloud computing IaaS. In order to achieve this objective, forecasting of cloud client requests was an important aspect towards achieving optimization since the cloud service providers, in this particular case Safaricom, would be able to use this as planning information when developing their storage infrastructure.

According to the experiments and supporting literature review, Support Vector Machine would be the proffered machine learning algorithm used as per the results observed from the results of the experiments of the research. It can be concluded therefore that through the use of support vector machines(SVM), we can develop predictions that can be used as a basis for improving on the efficiency of cloud service delivery and in turn optimization.

5.2 Recommendations

In this research, the researcher argues that the use of machine learning for the prediction of storage resource usage for the case of cloud computing is an approach worth adopting and the most accurate technique for this prediction would be support vector machine (SVM) learning technique.

5.3 Further work

The predictions were based on one tool that is DTREG and it is advised that other prediction tools be used such as WEKA, Hadoop and others .Further research is advised on developing dynamic models which can adopt the usage of cloud resources based on the requests from the users in real time. Also as an area for future research, the researcher suggests discussions and research on how machine learning techniques can be used to improve other areas of cloud computing that is PaaS and SaaS

Through the use of these predictions, clients can be appropriately advised and the cloud service provider can also do provisions for the right amounts of the given storage resource.

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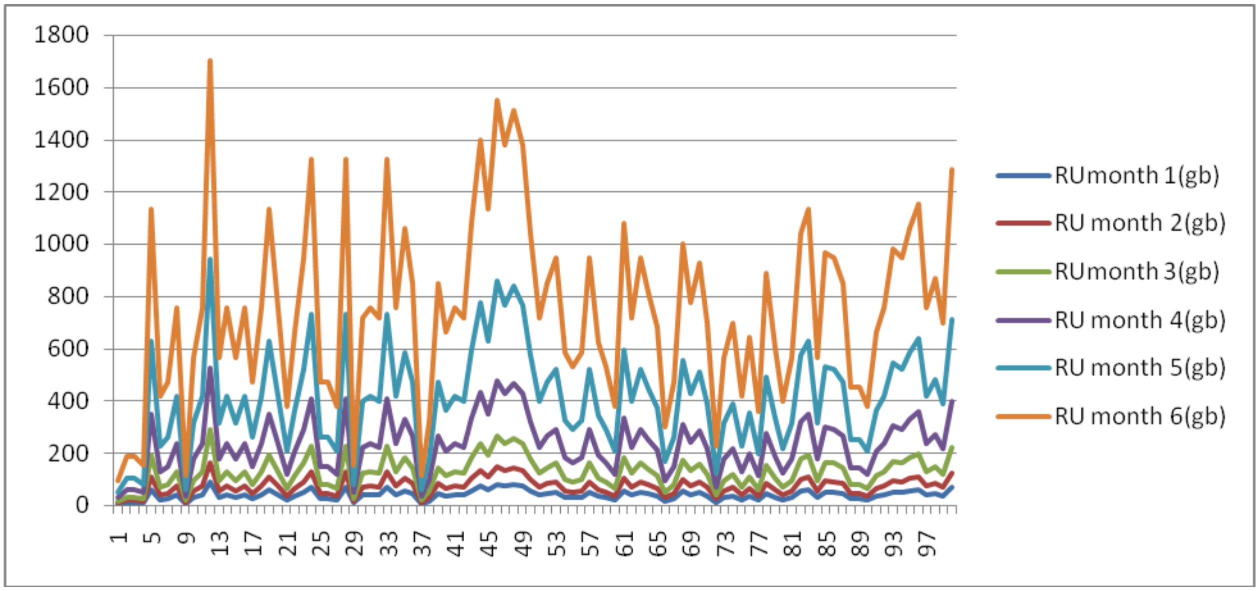
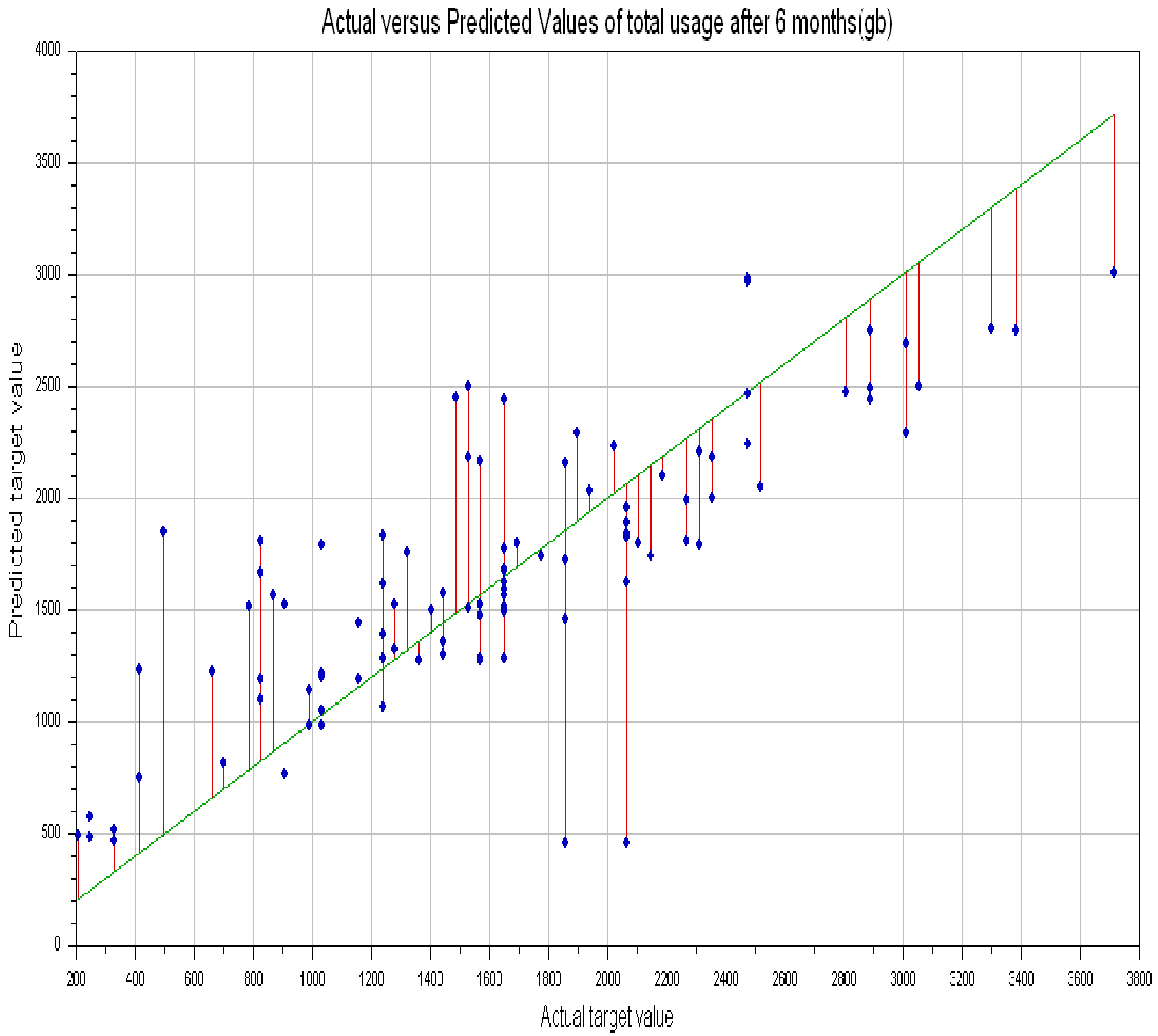
APPENDICES

Appendix 1:Screenshots for results

Comparative usage over six months



Actual versus predicted usage over six months



Appendix 2: Sample questions to Safaricom ltd. engineers

A) Are there optimization problems which Safaricom encounters with there cloud computing infrastructure?

The main optimization problems would be in terms of computer resource utilization (CPU, Memory and storage) usage.

There are defined limits that are set such a single customer should not use all/most of the resources on the server to himself as this would choke out other users.

B) How are they solved?

Servers' status are constantly monitored and growth pattern graphed (the growth pattern is fairly constant), so that either additional resources are added or new servers all together are deployed.

There are instances where the defined limits (web hosting) is too small for a customer, in such a case the S/W allows for the Safaricom admin to increase the specific customers limit, though this is done in very rare cases, as most likely the customer would be advised to optimize their application to fit within the defined limits

C) Does Safaricom manage their own platform and if they do, what approach is used to manage cloud resource?

We manage our own platforms on both IAAS and web hosting......(not sure how to answer the approach question)

D) What Softwares are used to achieve the cloud management?

For IAAS we require to virtualize our environment, in this case we use VMware as our hypervisor.

We use cpanel for our webhosting platform.

We also have monitoring solutions such as solar winds to monitor the servers and applications.

Appendix 3:Sample dataset experimented upon

RESOURCE REQUESTED(gb)	total usage after 6 months(gb)	no. of users	type of service
1000	206.3	248	storage
2000	412.7	249	storage
3500	412.7	146	storage
1000	330.1	294	storage
10000	2475.9	107	storage
2000	907.8	227	storage
3000	1031.6	66	storage
5000	1650.6	260	storage
1000	247.6	264	storage
4000	1238	228	storage
5000	1650.6	152	storage
10000	3713.9	77	storage
3000	1238	186	storage
4500	1650.6	64	storage
4000	1238	127	storage
5000	1650.6	104	storage
3000	1031.6	202	storage
4000	1650.6	232	storage
10000	2475.9	120	storage
8000	1650.6	129	storage
3000	825.3	68	storage
4000	1444.3	157	storage
5000	2063.3	154	storage

8000	2888.6	88	storage
2500	1031.6	141	storage
3000	1031.6	50	storage
5000	825.3	117	storage
9000	2888.6	83	storage
1000	330.1	221	storage
4000	1568.1	227	storage
5000	1584.1	180	storage
10000	3755.6	388	storage
6500	2036.7	222	storage
3500	729.2	105	storage
3000	500.8	86	storage
4000	958.9	124	storage
3000	535.3	89	storage
4000	983.2	127	storage
10500	4021.7	415	storage
10000	3804.6	393	storage
4500	1082.8	135	storage
3000	572.3	92	storage
4500	1091.2	136	storage
4000	828.5	113	storage
4000	942.2	123	storage
3000	463.8	83	storage
4000	980.3	126	storage
3000	494.1	86	storage
8500	2937.1	307	storage
8000	2572.7	272	storage
4000	926.9	122	storage
6000	1732.4	193	storage
2000	211.3	64	storage
14000	5539.7	570	storage

3000	470.7	84	storage
5000	1340.5	158	storage
3500	645.4	98	storage
4500	1027.3	130	storage
3000	569.7	92	storage
6500	1935.8	212	storage
5000	1249.7	150	storage
4500	1166.8	143	storage
6500	2011.3	219	storage
4000	924.1	121	storage
6500	2011.4	219	storage
4000	918.3	121	storage
5000	1358.1	160	storage
6000	1746.3	195	storage
3000	489.3	85	storage
10000	3484.3	361	storage
5500	1562.7	178	storage
7000	2135.6	231	storage
6500	1865.3	206	storage
4500	1147.8	141	storage
5500	1494.1	172	storage
10000	3662.6	379	storage
3500	648.2	98	storage
5000	1294.5	154	storage
4000	954.8	124	storage
5000	1207.9	146	storage
10000	1594.1	264	storage
6500	3765.6	228	storage
3500	2046.7	152	storage
3000	739.2	77	storage
4000	510.8	186	storage

3000	968.9	64	storage
4000	545.3	127	storage
10500	993.2	104	storage
10000	4031.7	202	storage
4500	3814.6	232	storage
3000	1092.8	120	storage
4500	582.3	129	storage
4000	1101.2	68	storage
4000	838.5	157	storage
3000	952.2	154	storage
4000	473.8	88	storage
3000	990.3	141	storage
8500	504.1	50	storage
8000	2947.1	117	storage
4000	2582.7	83	storage
6000	936.9	221	storage
2000	1742.4	227	storage
14000	221.3	180	storage
8000	5549.7	388	storage
10000	480.7	222	storage
4500	1350.5	105	storage
3000	655.4	86	storage
4500	1037.3	124	storage
4000	579.7	89	storage
4000	1945.8	127	storage
3000	1259.7	415	storage
4000	1176.8	393	storage
3000	2021.3	135	storage
8500	934.1	92	storage
8000	2021.4	136	storage
4000	928.3	113	storage

6000	1368.1	123	storage
2000	1756.3	83	storage
14000	499.3	126	storage
3000	3494.3	86	storage
5000	1572.7	307	storage
3000	2145.6	272	storage
5000	1875.3	122	storage
1000	1157.8	193	storage
5000	1504.1	64	storage
4500	3672.6	570	storage
8000	658.2	84	storage
6500	1304.5	158	storage
5000	964.8	98	storage
6000	1217.9	130	storage
5000	1589.1	92	storage
4000	3760.6	212	storage
5000	2041.7	150	storage
6000	734.2	143	storage
3000	505.8	219	storage
10000	963.9	121	storage
5500	540.3	219	storage
7000	988.2	121	storage
6500	4026.7	160	storage
4500	3809.6	64	storage
5500	1087.8	570	storage
10000	577.3	84	storage
3500	1096.2	158	storage
1000	833.5	98	storage
4000	947.2	130	storage
5000	468.8	92	storage
10000	985.3	212	storage

6500	499.1	150	storage
3500	2942.1	143	storage
3000	2577.7	219	storage
4000	931.9	121	storage
3000	1737.4	219	storage
4000	216.3	121	storage
10500	5544.7	160	storage
10000	475.7	195	storage
4500	1345.5	85	storage
3000	650.4	361	storage
4500	1032.3	178	storage
5000	574.7	231	storage
8500	1940.8	206	storage
5000	1254.7	141	storage
6000	1171.8	172	storage
9000	2016.3	379	storage
4500	929.1	98	storage
8000	2016.4	154	storage
4000	923.3	124	storage
10500	1363.1	146	storage
6000	1751.3	264	storage
5000	494.3	228	storage
7000	3489.3	152	storage
3000	1567.7	77	storage
4500	2140.6	186	storage
6000	1870.3	64	storage
4000	1152.8	127	storage
6000	1499.1	104	storage
8000	3667.6	202	storage
5000	653.2	232	storage
6000	1299.5	143	storage

9000	959.8	219	storage
8000	1212.9	121	storage
6000	1604.1	219	storage
4000	3775.6	121	storage
10000	2056.7	160	storage
4000	749.2	64	storage
8000	520.8	570	storage
5000	978.9	84	storage
4000	555.3	158	storage
3000	1003.2	98	storage
4000	4041.7	130	storage
5500	3824.6	92	storage
7000	1102.8	212	storage
5000	592.3	150	storage
5000	1111.2	143	storage
6000	848.5	219	storage
5500	962.2	121	storage
4000	483.8	219	storage
8000	1000.3	121	storage
7500	514.1	160	storage
8000	2957.1	154	storage
5000	2592.7	124	storage
3000	946.9	146	storage
6000	1752.4	264	storage
4000	231.3	228	storage
10000	5559.7	152	storage
4000	490.7	77	storage
8000	1360.5	186	storage
5000	665.4	64	storage
4000	1047.3	127	storage
3000	589.7	104	storage

4000	1955.8	202	storage
5500	1269.7	232	storage
7000	1186.8	143	storage
5000	2031.3	219	storage
4000	944.1	121	storage
4500	2031.4	219	storage
6000	938.3	121	storage
3000	1378.1	160	storage
4500	1766.3	64	storage
7000	509.3	570	storage
8000	3504.3	84	storage
7500	1582.7	92	storage
6500	2155.6	212	storage
6000	1885.3	150	storage
6000	1167.8	143	storage
7500	1514.1	219	storage
8000	3682.6	121	storage
5000	668.2	219	storage
6000	1314.5	121	storage
5500	974.8	160	storage
5000	1227.9	154	storage
4000	1599.1	124	storage
4500	3770.6	146	storage
3000	2051.7	264	storage
4500	744.2	228	storage
4000	515.8	152	storage
4000	973.9	77	storage
3000	550.3	186	storage
4000	998.2	64	storage
3000	4036.7	127	storage
8500	3819.6	104	storage

8000	1097.8	202	storage
4000	587.3	232	storage
6000	1106.2	130	storage
2000	843.5	92	storage
14000	957.2	212	storage
3000	478.8	379	storage
5000	995.3	98	storage
8500	509.1	154	storage
6000	2952.1	124	storage
5000	2587.7	146	storage

Appendix 4:DTREG user manual screen shots

When you launch DTREG, its main screen displays:

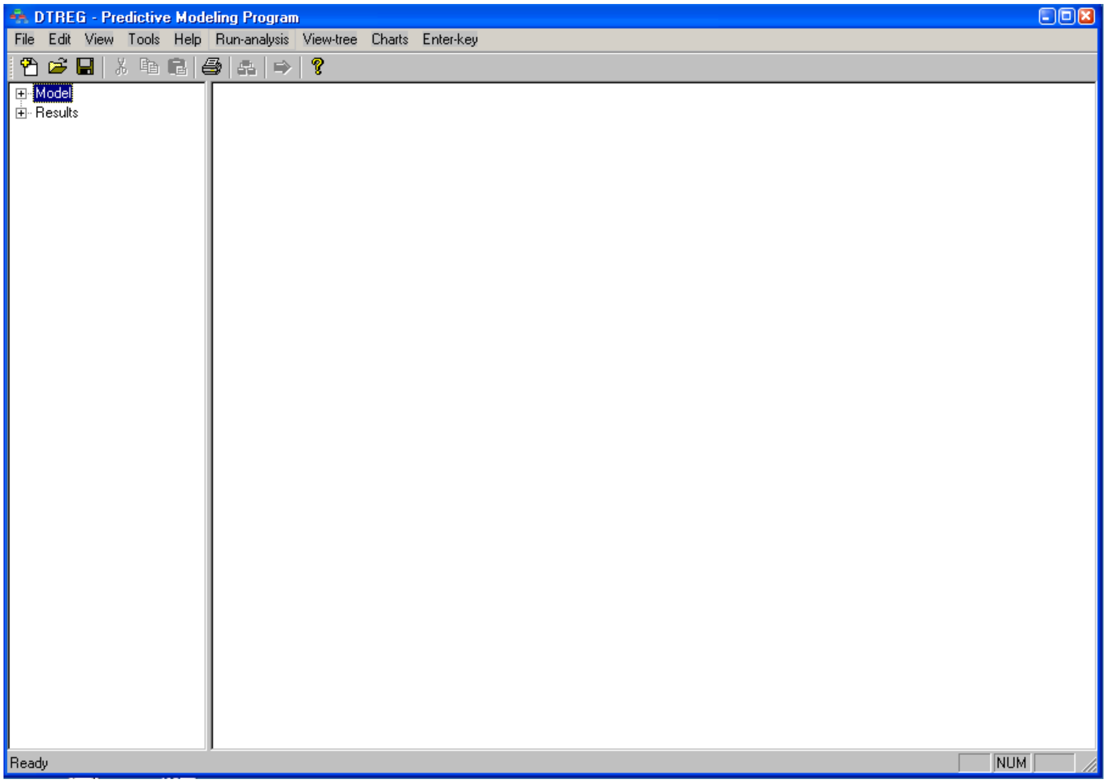


Figure 9-DTREG-main screen

From this screen, you can

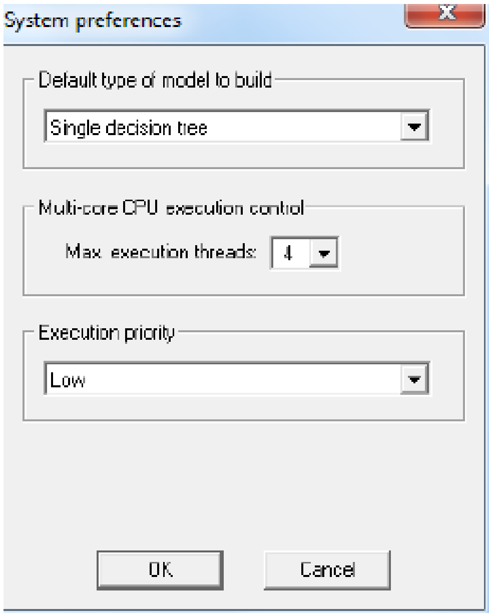
i. Create a new project to build a model by clicking

ii. Open an existing project by clicking

iii. Set options and enter your registration key.

Setting DTREG preferences

To set DTREG preferences, click “Tools” on the menu bar and select “Preferences” from the dropdown menu.



System preferences

Default type of model to build: Single decision tree

Multi-core CPU execution control

Max. execution threads: 4

Execution priority: Low

Figure 10-DTREG screen for setting prefferences

Default type of model to build: Select which type of model you would like DTREG to create for new projects (single tree, SVM neural network, etc.). You can always change the type of a model later by modifying its properties.

Max. execution threads: Specify how many execution threads you want DTREG to use during its computations. If you have a multi-CPU system, you can increase the speed of calculation by allowing DTREG to use more than one CPU, but this will place a heavier load on your system.

Execution priority: Specify the preferred execution for DTREG to use during an analysis. Currently the execution priority is only applied to neural network training processes.

Loading the training file

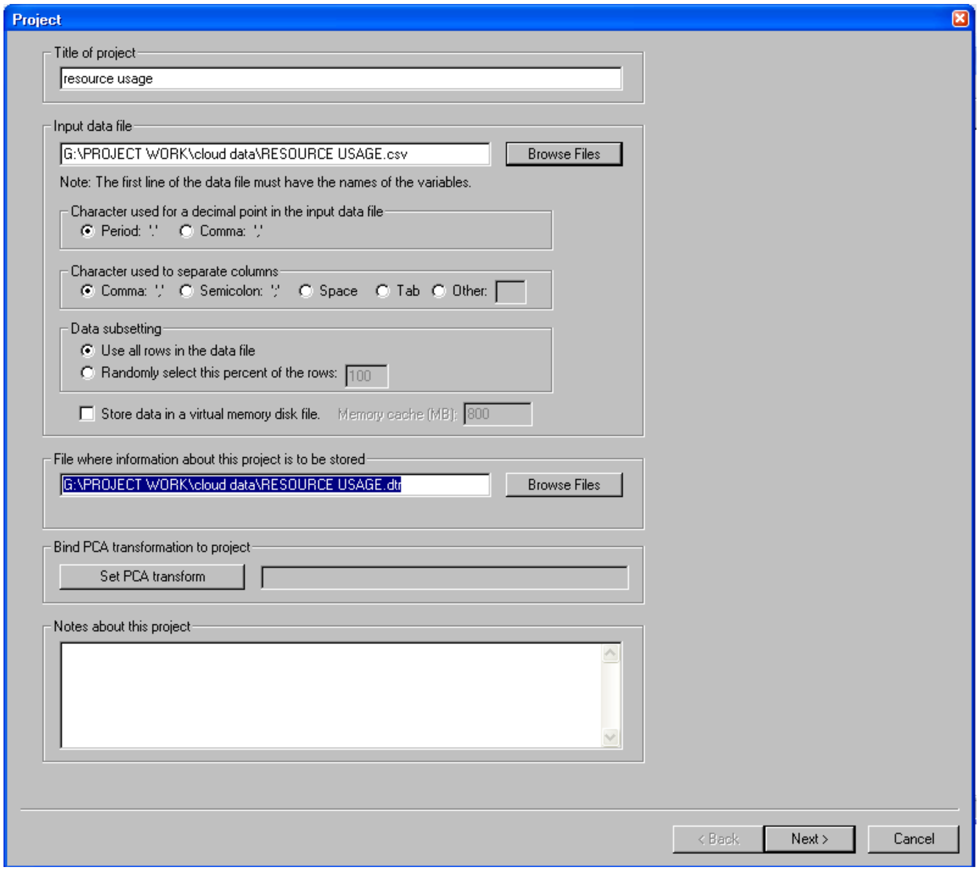
The first step in building a model the following are required:

Input data file –Specify the device, folder and name of the file containing the input (Learning) dataset to be used to build the model. The data must be in a comma separated value (CSV) file with the names of the variables on the first line.

Character used for a decimal point in the input data file – Select whether a period or a comma will be used to indicate the decimal point in numeric values in the input data file.

Character used to separate columns – Select the character that will be used to separate columns in the input file. The default separator is a comma.

File where information about this project is to be stored – Specify the name of the project files where DTREG will store parameters and computed values for the project. DTREG project files are stored with the type **—.dtr**.



Project

Title of project: resource usage

Input data file: G:\PROJECT WORK\cloud data\RESOURCE USAGE.csv

Note: The first line of the data file must have the names of the variables.

Character used for a decimal point in the input data file: ● Period: '.' ○ Comma: ','

Character used to separate columns: ● Comma: ',' ○ Semicolon: ';' ○ Space ○ Tab ○ Other:

Data subsetting: ● Use all rows in the data file ○ Randomly select this percent of the rows: 100

□ Store data in a virtual memory disk file. Memory cache (MB): 800

File where information about this project is to be stored: G:\PROJECT WORK\cloud data\RESOURCE USAGE.dtr

Bind PCA transformation to project

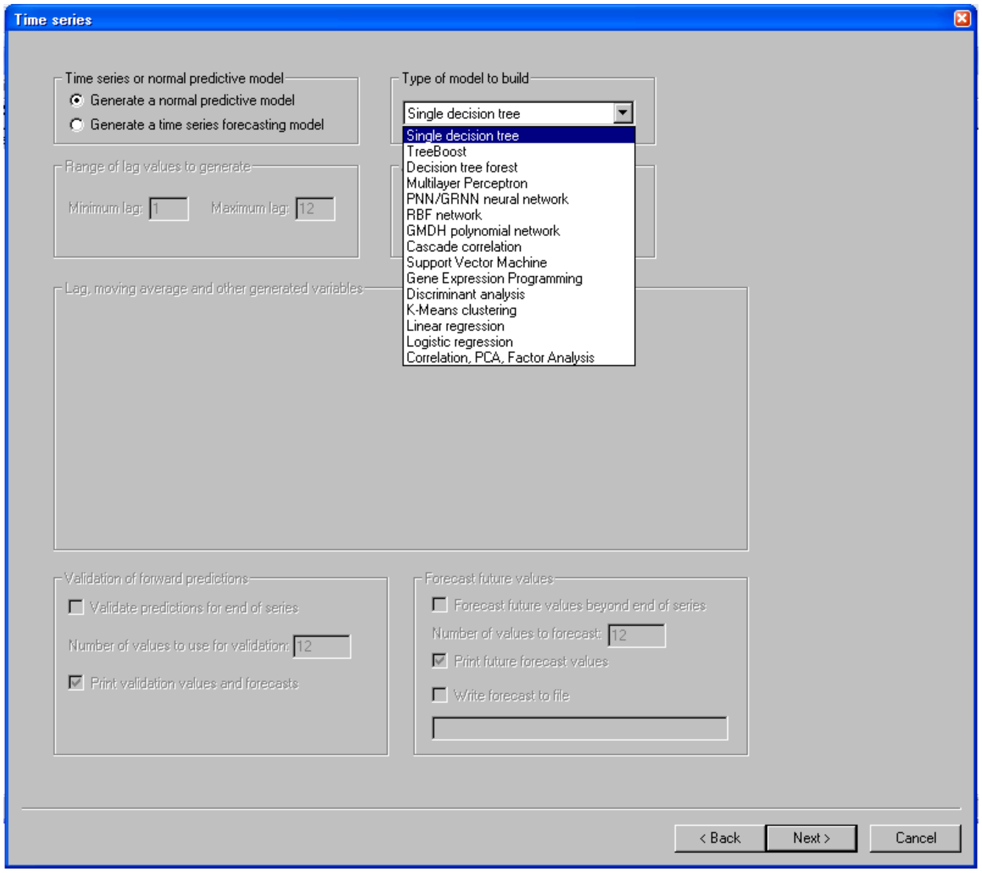
Notes about this project

Figure 11-DTREG screen for loading training data files and specifying storage location for outputs

The file loaded is the data used for training. The data is divided by the system into the two data sets i.e. training set and validation set.

Testing the various prediction techniques

<u>Selecting the prediction technique</u>



Time series

Time series or normal predictive model

● Generate a normal predictive model

○ Generate a time series forecasting model

Type of model to build: Single decision tree

Range of lag values to generate

Minimum lag: 1 Maximum lag: 12

Lag, moving average and other generated variables

Validation of forward predictions

□ Validate predictions for end of series

Number of values to use for validation: 12

☑ Print validation values and forecasts

Forecast future values

□ Forecast future values beyond end of series

Number of values to forecast: 12

☑ Print future forecast values

□ Write forecast to file

Figure 12-DTREG screen for selecting the prediction model

The third step involves selection of a prediction model to be studied. Choose normal predictive model for (DT, SVM, MLP, and K-means clustering).

Assigning the classes

The fourth step involves selection of variables.

Classes of Variables

Specify the classes of variables to performing analyses:

Target variable: The target variable is the variable whose values are to be modeled and predicted by other variables. It is analogous to the dependent variable. There must be one and only one target variable. Our target variable is class index (resource usage) as shown on the table below and should be categorically.

Predictor variable: A predictor variable is a variable whose values will be used to predict the value of the target variable. It is analogous to the independent variables. There must be at least one predictor variable specified, and there may be many predictor variables.

Our predictor variables were:

- Resource requested (RQ)

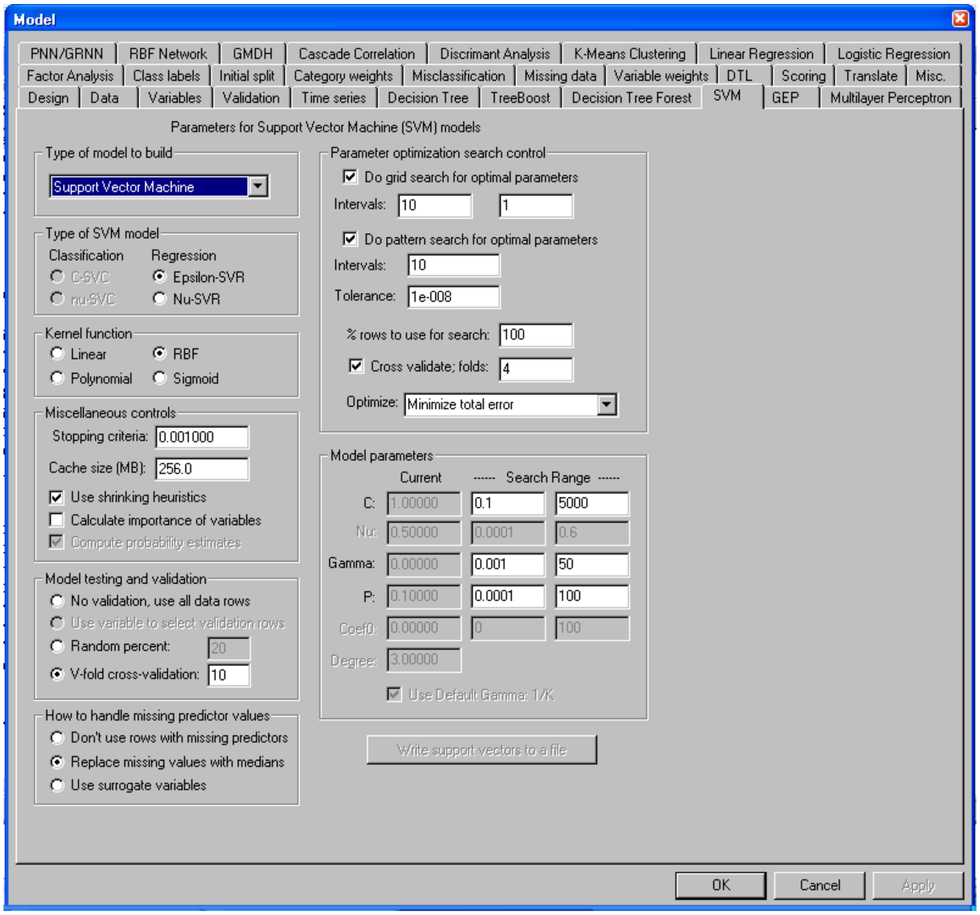
The predictor variables are continuous

Model testing and validation

Before running a model enabled the following settings that will be used to measure the performance of the models:

Cross-validation Control Variable

This is used to evaluate the quality of a model it’s assigned a random set of rows to each validation fold after stratifying on the target variable.


Model
PNN/GRNN | RBF Network | GMDH | Cascade Correlation | Discriminant Analysis | K-Means Clustering | Linear Regression | Logistic Regression
Factor Analysis | Class labels | Initial split | Category weights | Misclassification | Missing data | Variable weights | DTL | Scoring | Translate | Misc.
Design | Data | Variables | Validation | Time series | Decision Tree | TreeBoost | Decision Tree Forest | SVM | GEP | Multilayer Perceptron
Write support vectors to a file
OK
Cancel
Apply

Parameters for Support Vector Machine (SVM) models

Type of model to build: Support Vector Machine

Type of SVM model
- Classification: ○ C-SVC, ○ nu-SVC
- Regression: ● Epsilon-SVR, ○ Nu-SVR

Kernel function: ○ Linear ● RBF ○ Polynomial ○ Sigmoid

Miscellaneous controls
- Stopping criteria: 0.001000
- Cache size (MB): 256.0
- ☑ Use shrinking heuristics
- □ Calculate importance of variables
- ☑ Compute probability estimates

Model testing and validation
- ○ No validation, use all data rows
- ○ Use variable to select validation rows
- ○ Random percent: 20
- ● V-fold cross-validation: 10

How to handle missing predictor values
- ○ Don't use rows with missing predictors
- ● Replace missing values with medians
- ○ Use surrogate variables

Parameter optimization search control
- ☑ Do grid search for optimal parameters
- Intervals: 10 1
- ☑ Do pattern search for optimal parameters
- Intervals: 10
- Tolerance: 1e-008
- % rows to use for search: 100
- ☑ Cross validate; folds: 4
- Optimize: Minimize total error

Model parameters

	Current	Search Range	
C:	1.00000	0.1	5000
Nu:	0.50000	0.0001	0.6
Gamma:	0.00000	0.001	50
P:	0.10000	0.0001	100
Coef0:	0.00000	0	100
Degree:	3.00000		

☑ Use Default Gamma: 1/K

Figure 13-DTREG screen for setting model variables

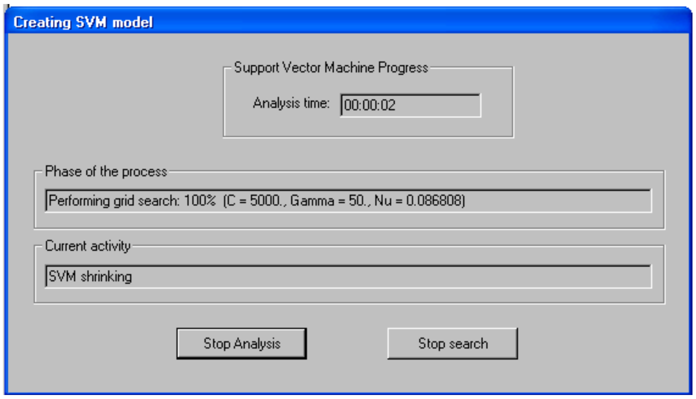
Model validation record

Validation data row report file – If you enable this option and specify a file name in the edit field, then DTREG will write a record to the file showing which rows were used for validation, and it will show the predicted value for each validation row. Each row in the file has 4 columns: (1) the data row number , (2) the actual value of the target variable, (3) the predicted value of the target variable, and (4) an indication of correct/incorrect class residual value if doing regression

Run the model

Once you have done all the steps you can then tell DTREG to perform an analysis.

While an analysis is running, a progress screen will be displayed



Analysis time: 00:00:02

Performing grid search: 100% (C = 5000., Gamma = 50., Nu = 0.086808)

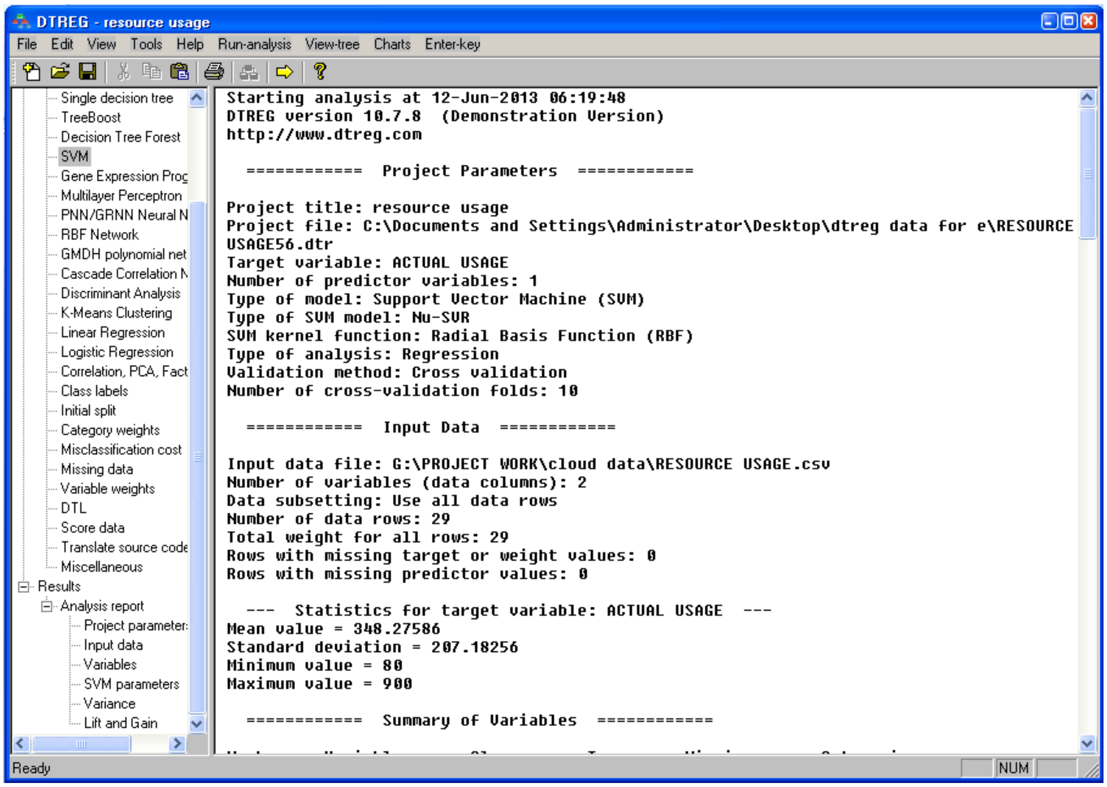
SVM shrinking

Figure 14-DTREG screen for model creation

Results of analysis

When the model has completed its execution the results are displayed. There are several major sections in the report.

The Project Parameters section of the report displays a summary of the options and parameters selected for the model.



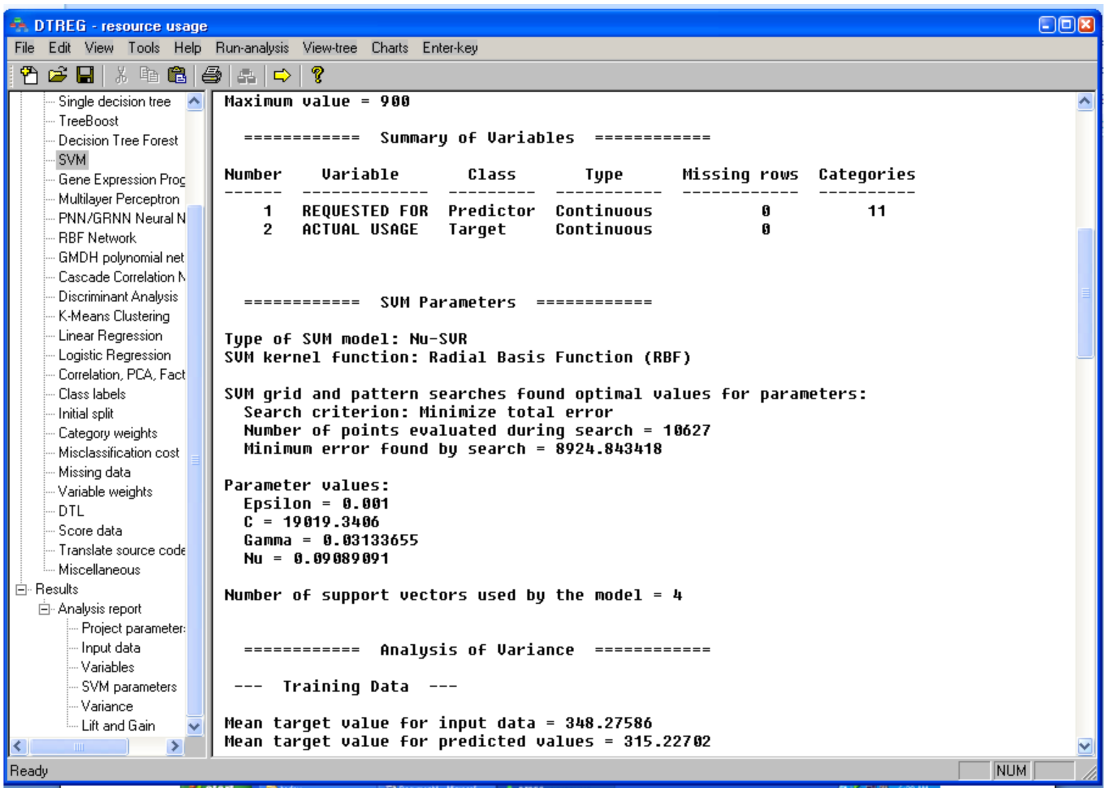
```
Starting analysis at 12-Jun-2013 06:19:48
DTREG version 10.7.8  (Demonstration Version)
http://www.dtreg.com

  ============  Project Parameters  ============

Project title: resource usage
Project file: C:\Documents and Settings\Administrator\Desktop\dtreg data for e\RESOURCE
USAGE56.dtr
Target variable: ACTUAL USAGE
Number of predictor variables: 1
Type of model: Support Vector Machine (SVM)
Type of SVM model: Nu-SVR
SVM kernel function: Radial Basis Function (RBF)
Type of analysis: Regression
Validation method: Cross validation
Number of cross-validation folds: 10

  ============  Input Data  ============

Input data file: G:\PROJECT WORK\cloud data\RESOURCE USAGE.csv
Number of variables (data columns): 2
Data subsetting: Use all data rows
Number of data rows: 29
Total weight for all rows: 29
Rows with missing target or weight values: 0
Rows with missing predictor values: 0

  ---  Statistics for target variable: ACTUAL USAGE  ---
Mean value = 348.27586
Standard deviation = 207.18256
Minimum value = 80
Maximum value = 900

  ============  Summary of Variables  ============
```

Figure 15-DTREG screen for results report

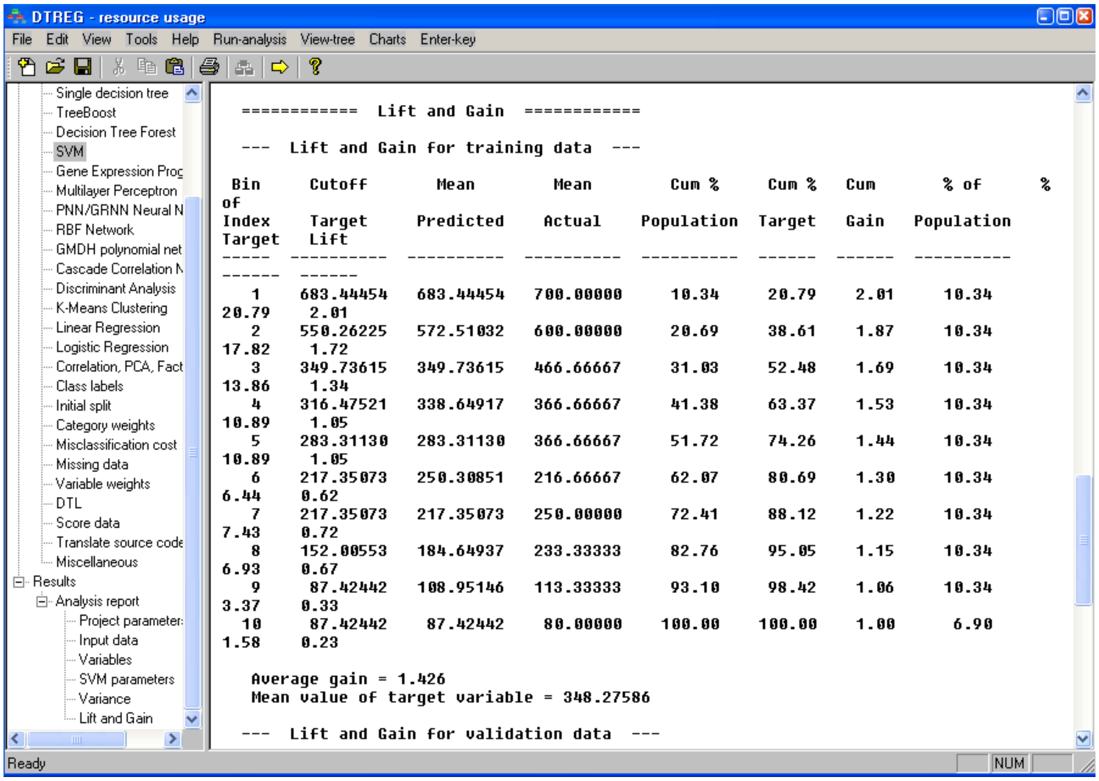
Input data section

The Input Data section displays information about the input data file used to construct the model. The entry for ―Rows with missing target or weight values indicates the number of rows that were discarded because these variables had missing values.

Summary of variables



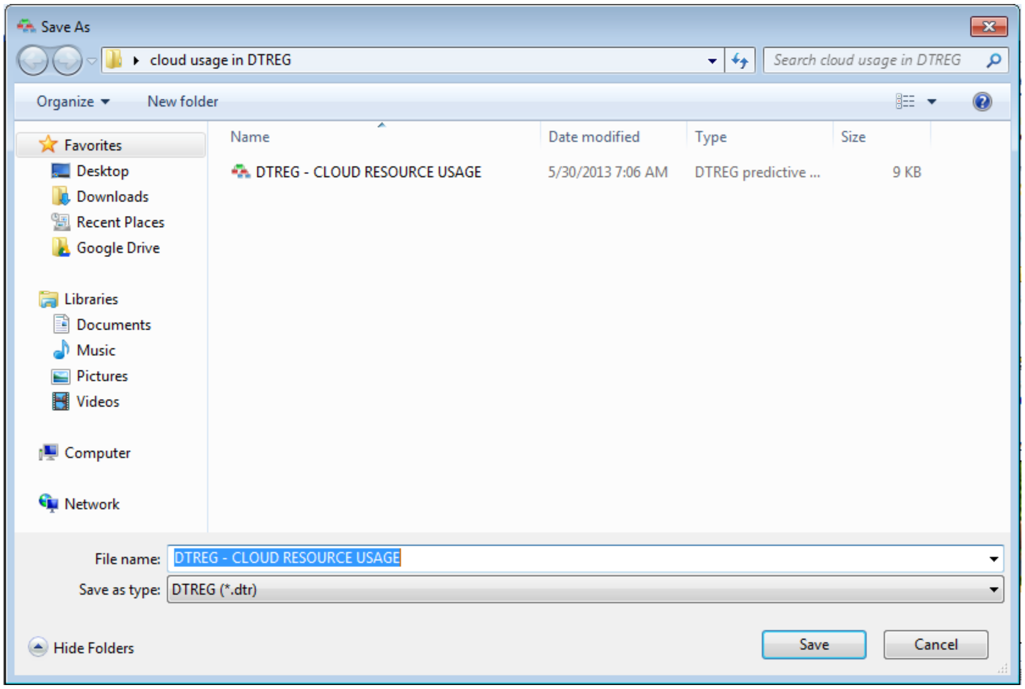
```
Maximum value = 900

  ============  Summary of Variables  ============

Number    Variable       Class       Type      Missing rows  Categories
------  -------------  ---------  -----------  ------------  ----------
    1   REQUESTED FOR  Predictor  Continuous             0          11
    2   ACTUAL USAGE   Target     Continuous             0



  ============  SVM Parameters  ============

Type of SVM model: Nu-SVR
SVM kernel function: Radial Basis Function (RBF)

SVM grid and pattern searches found optimal values for parameters:
  Search criterion: Minimize total error
  Number of points evaluated during search = 10627
  Minimum error found by search = 8924.843418

Parameter values:
  Epsilon = 0.001
  C = 19019.3406
  Gamma = 0.03133655
  Nu = 0.09089091

Number of support vectors used by the model = 4


  ============  Analysis of Variance  ============

 ---  Training Data  ---

Mean target value for input data = 348.27586
Mean target value for predicted values = 315.22702
```



```
  ============  Lift and Gain  ============

  ---  Lift and Gain for training data  ---

 Bin     Cutoff       Mean        Mean        Cum %      Cum %   Cum       % of       %
of
Index    Target     Predicted     Actual    Population  Target   Gain    Population
Target   Lift
-----  ----------  ----------  ----------  ----------  ------  ------  ----------
------   ------
   1    683.44454   683.44454   700.00000     10.34     20.79    2.01      10.34
20.79    2.01
   2    550.26225   572.51032   600.00000     20.69     38.61    1.87      10.34
17.82    1.72
   3    349.73615   349.73615   466.66667     31.03     52.48    1.69      10.34
13.86    1.34
   4    316.47521   338.64917   366.66667     41.38     63.37    1.53      10.34
10.89    1.05
   5    283.31130   283.31130   366.66667     51.72     74.26    1.44      10.34
10.89    1.05
   6    217.35073   250.30851   216.66667     62.07     80.69    1.30      10.34
6.44    0.62
   7    217.35073   217.35073   250.00000     72.41     88.12    1.22      10.34
7.43    0.72
   8    152.00553   184.64937   233.33333     82.76     95.05    1.15      10.34
6.93    0.67
   9     87.42442   108.95146   113.33333     93.10     98.42    1.06      10.34
3.37    0.33
  10     87.42442    87.42442    80.00000    100.00    100.00    1.00       6.90
1.58    0.23

   Average gain = 1.426
   Mean value of target variable = 348.27586

  ---  Lift and Gain for validation data  ---
```

Saving the prediction file

After completion of the analysis the project can then be saved for later referencing.



Name	Date modified	Type	Size
DTREG - CLOUD RESOURCE USAGE	5/30/2013 7:06 AM	DTREG predictive ...	9 KB

File name: DTREG - CLOUD RESOURCE USAGE

Save as type: DTREG (*.dtr)