

**Efficient Parallel Data Processing  
in the Cloud**

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# Chapter 1

## Introduction

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### 1.1 Project Aim

Large scale data processing is an emerging trend in Computing, with benefits to both academia and industry. The aim of this project is to investigate the challenges of large scale parallel data processing, discuss the benefits of Cloud Computing and investigate how the efficiency of large scale data processing may be improved.

This project will aim to provide a reasoned and objective evaluation of the efficiency of data processing techniques, whilst comparing current state of the art tools and technologies with newer research in the field.

Specifically, the data processing tools Hadoop and Nephele will be compared, allowing comparison of the individual tools, and a wider discussion of the pros and cons of the MapReduce and PACT programming paradigms.

#### 1.1.1 Research Questions

The project aims to answer the following questions:

- Does PACT overcome the inherent disadvantages of the MapReduce paradigm?
- How well does Nephele perform MapReduce tasks?
- How do Hadoop and Nephele perform in a highly elastic Cloud Computing environment?

## 1.2 Objectives

The objectives of the project are:

- Investigate Cloud Computing, Big Data and other relevant background trends
- Design a series of experiments to determine the efficiency of data processing technologies
- Implement the experiments for both Hadoop and Nephele
- Evaluate the experiment results to draw meaningful conclusions to the research questions

## 1.3 Methodology

The project will be broken into three main phases. The order to the phases provides a structured approach to the project, and completion of each phase ensures the project is completed in a methodical manner. The **Background Research** section will provide a comprehensive literature review to provide context to the project. This will be followed by a phase of **Experimentation**, which will aim to test the necessary factors of Hadoop and Nephele to answer the research questions. Finally, the **Evaluation** phase will evaluate the results of the experiments and the project as a whole.

The phases of the project will be performed according to Agile principles. Work will be carried out in weekly sprints, with clearly defined targets for each sprint. Supervisor meetings will be used as an opportunity to reflect on the achievements and shortcomings of the previous week, and to set targets for the upcoming sprint.

### 1.3.1 Background Research

The background research will aim to provide context for the project by surveying the current research landscape. It will summarise the fundamental concepts underlying the project and give a strong theoretical foundation for the rest of the project.

The first section of the background research will focus on Cloud Computing. It will explore the principles of the cloud, the service and deployment models and the technologies which make the cloud possible. It will also look at the unique advantages that the cloud provides in data processing scenarios.

The second segment of the background research will look in to Big Data and what challenges it introduces. An overview will be given of tools and techniques which have been developed to process Big Data, including Hadoop and Nephele.

### 1.3.2 Experimentation

Experiments will be designed to test the efficiency of data processing tools in relevant situations. This will require identifying relevant areas of interest, and deriving scenarios which will test the efficiency

of Hadoop and Nephele. The experiments should be designed to take into account the various different problems that data processing tools are required to solve and to provide findings for the research questions.

As part of the experiment design, a hypothesis will be produced.

The experiments will be implemented and executed, in order to provide results which can be used to answer the research questions.

### **1.3.3 Evaluation**

The project can be evaluated on various factors.

A technical evaluation will be carried out to analyse the results of the experiments. It will compare the efficiency of Hadoop and Nephele, referring to data obtained in the experimentation phase. The results will be compared to existing research (obtained during the background research) and the hypothesis, and any discrepancies will be discussed.

An evaluation will also be carried out to determine whether the aims and objectives of the project have been met. This will involve determining whether the research questions have been answered in a satisfactory manner, and determining the relevance of the project in regards to existing literature and how it contributes to the research landscape. Any future scope for research will be identified.

The methodology and management of the project will also be evaluated to identify areas of improvement in project management. This evaluation will be carried out in the personal reflection.

## **1.4 Schedule**

The project schedule will be created around a set of fixed milestones in the project process. Work will be allocated in weekly sprints to ensure that the relevant work is completed in time for each milestone. Work will be prioritised so that scope can be cut to meet a milestone if required.

### **1.4.1 Milestones**

There are a series of milestones which must be met throughout the project. This provides a framework for the project plan, as necessary tasks must be completed before the milestones.

#### **1. Submission of Aims & Objectives**

The Aims & Objectives of the project must be decided, which is crucial in setting the scope and direction for the rest of the project.

#### **2. Presentation to the Distributed Systems and Services Group**

The presentation to the Distributed Systems and Services group provides an opportunity to get early feedback on the project, and present much of what will be present in the mid year report. In order to present the project, a sufficient amount of content must be prepared. By this point a

substantial amount of background research should have been carried out, and early ideas about experimental design should be formed.

### 3. Mid-Year Project Report

The Mid-Year Project Report is a chance to get feedback from the assessor about the direction and progress of the project. By this stage the background research should be completed, and should demonstrate that necessary steps have been taken to understand the problem. The Aims & Objectives should be clearly defined, with a set of deliverables, a methodology, and a schedule. At this point experimental design will not have been completed, but the Mid-Year Report should give indications about the type of experiments that will be executed and why they were chosen. Finally, evidence of basic implementation should be shown, to demonstrate knowledge of the tools required for experiment implementation.

### 4. Progress Meeting

The progress meeting occurs in the late stages of the project, so at this point most of the work should be completed. Experiments should have been implemented and performed, and code should be available for inspection.

### 5. Final Report Submission

The final report submission marks a point where all work on the project has to be complete.

## **1.5 Deliverables**

The project will deliver 2 things.

1. An evaluation of the efficiency of Hadoop and Nephele in various data processing situations
2. Code for experiments, designed to test the efficiency of Hadoop and Nephele

## Chapter 2

# Background Research

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This chapter is intended to give an overview of the current research landscape, and to summarise the core technologies and concepts which form a basis for this project. The chapter will discuss trends toward Cloud Computing, how it is relevant to Data Processing, and key technologies which have been developed in this area, giving a foundation for further investigation into the efficiency of Data Processing techniques and how they are impacted by the Cloud.

### 2.1 Cloud Computing

Cloud Computing is the latest major infrastructure paradigm which looks to deliver on the promise of Utility Computing. In practice, the term ‘Cloud Computing’ is ambiguous. Whilst no clear definition exists many experts agree that the cloud exhibits the core benefits of Utility Computing such as elasticity and scalability, whilst making heavy use of virtualisation and pay-per-usage business models [29].

Elasticity in clouds refers to the ability for a user to dynamically select the amount of computing resources they require, allowing them to scale their applications according to demand. The resources that can be acquired are essentially limitless from the user’s perspective [21].

Elasticity represents a dramatic shift from the ‘traditional’ method of building and deploying applications. Rather than purchasing and provisioning hardware and acquiring physical space (such as a data centre), a user can use a Cloud Service Provider. This allows for greater flexibility in business and application development, as users can cope with unpredictable or inconsistent levels of demand. An example of where this flexibility would benefit a company is in the case of an online store. A store may receive fluctuating traffic throughout a year, such as being particularly busy around the Christmas



period. It would be economically inefficient for the store to purchase extra servers to cope with demand over the festive period, as they would be redundant for the majority of the year, but they must improve hardware capability in order to take advantage of the extra business. The inherent flexibility from the elasticity of the cloud would allow the store to simply acquire new computing capacity from their Cloud Service Provider on a temporary basis, giving them the capability of accommodating with the peak traffic but not using (or paying for) the extra resources when they are not needed. Having this scalability is seen as a core benefit of Cloud Computing.

A Cloud Service Provider is an organisation that provides access to Cloud Computing resources. They manage the underlying hardware, and typically provide APIs and other methods for a user to manage their resources. Some of the largest Cloud Service Providers are Amazon through AWS (Amazon Web Services), Microsoft through Windows Azure and Google through Google Apps.

A Cloud Service Provider does not have to be an external organisation, but when they are they typically use pay-per-usage business models. Rather than pay a fixed monthly cost, or have a one-off license fee, customers will pay the Cloud Service Provider for the resources they use (usually on a per-hour basis). For example, a 'Medium' size Virtual Machine costs 0.077 an hour from Windows Azure [22]. This allows businesses to only pay for the resources that they need.

## **2.1.1 Related Ideas**

### **2.1.1.1 Utility Computing**

Utility Computing is the idea that households and businesses could outsource their demand to external companies, who provide the relevant amount of service on a pay-per-usage basis. Customers would access computing resources over a network, and would pay for the length of computing time that they use.

This is analogous to other utilities such as Gas or Electricity. In the case of Electricity, power is provided from the National Grid and the customer pays for how much they use. This allows a customer change the amount of power they require without having to pay a fixed cost (for example, using less electricity when they are on holiday).

Utility Computing is an established concept, with leading thinkers such as Leonard Klienrock (part of the original ARPANET project) referencing it as early as 1969 [20]. Various technologies have emerged which offer some attributes associated with utility computing, with Grids and Clouds appearing to be the most promising [13].

### **2.1.1.2 Virtualisation**

Virtualisation is one of the key enabling technologies behind Cloud Computing. It abstracts away the details of the physical hardware and allows Cloud Service Operators to run several virtual machines on one physical machine [36], completely independently of one another. This allows for customers applications and the physical hardware to be consolidated, utilising resources more efficiently and

making it financially feasible to run a cloud [17].

The configurability afforded by virtualisation is another property essential to Cloud Computing. It allows Cloud Service Providers to support a diverse range of applications, which may have different requirements (high compute, high memory, etc). Virtualisation allows this to be achieved, as it would be prohibitively costly at hardware level [17].

The reliability of a cloud can also be improved through the use of virtualisation techniques. Virtual Machines can be backed up, migrated and replicated simply, allowing applications to recover from hardware failure.

## **2.2 Cloud Computing Service Models**

Depending on the scenario, the Cloud offers several different service models. These models allow for clients to provision services in a different manner, depending on what they need from the cloud.

The different service models provide different levels of abstraction for the user. In Infrastructure as a Service, the user has full control over the machines that they acquire from the Cloud Service Provider, where in Software as a Service they are given less control, and need not worry about the underlying hardware whatsoever.

### **2.2.1 Infrastructure as a Service**

Infrastructure as a Service (IaaS) provides an abstraction on top of a virtualisation platform, so that the client does not need to worry about what method of virtualisation is being used, and does not have to learn about the underlying technologies [8].

Clients can request Virtual Machines in varying configurations, and a Virtual Infrastructure Manager will provision an appropriate Virtual Machine on a physical machine which has capacity. In addition to allowing users to provision virtual machines, IaaS systems may allow a user to configure other infrastructure elements, such as virtual networks.

This provides a great deal of control to the user, as they are essentially renting a machine of a requested specification for a short period of time. They are free to install whatever Operating System and software on the machine as required, and can configure it in essentially any way.

An example of an Infrastructure as a Service provider would be Amazon EC2 [6]. Amazon provide a variety of different Virtual Machine types, including those specialising in High Performance Computing or applications requiring a large amount of memory. Virtual Machines can use a range of images provided by Amazon (including Windows and various distributions of Linux), or users can create and upload their own custom Virtual Machine images.

### **2.2.2 Platform as a Service**

Platform as a Service (PaaS) is a higher level abstraction which allows applications to be built and deployed without worrying about the underlying Operating System or runtime environment [19]. The

user still specifies the resources required, but no longer has to manually manage the virtual machines. The Cloud Service Provider will maintain the machines, providing the necessary software (Operating Systems, Web Servers, etc) and updating them frequently.

The advantage of PaaS is that it allows users to deploy their own applications, without having to worry about maintaining the underlying infrastructure. Whilst this decreases the control the user has over the deployment environment, it reduces the complexity of managing the infrastructure themselves.

PaaS offerings may also provide supplementary services to users, such as health and availability monitoring, or auto-scaling.

Windows Azure is an example of a Platform as a Service provider [23]. Whilst they provide Infrastructure as a Service offerings, they also provide Platform as a Service capabilities through Windows Azure Web Sites. Windows Azure Web Sites allow users to upload applications written in a variety of web technologies (ASP.NET, Python, PHP, Node.js) and have them hosted in the Windows Azure runtime environment. This means the client does not manually have to manage web servers, frameworks and other necessary technologies.

### **2.2.3 Software as a Service**

Software as a Service (SaaS) refers to providing access to applications over the internet on-demand [36]. Software is centrally hosted by the Cloud Service Provider, and clients can access the application through a web browser or other form of client. As the software is centrally hosted, Cloud Service Providers can handle updating the software for all users, ensuring all users benefit from bug fixes or additional features.

Software as a Service applications can reduce the cost of deploying and using software for an organisation as they don't have to purchase their own hardware, install and configure software, and can avoid having technical support staff. An example of a successful Software as a Service application is Salesforce [26]. Salesforce is a Customer Relationship Management tool which charges organisations per user, making it a viable choice for small businesses. Salesforce can be accessed through a web browser, enabling customers to use their software regardless of location or device.

## **2.3 Cloud Computing Deployment Models**

Cloud Services can be deployed in several different ways. The National Institute of Science and Technology defines 4 Cloud Computing deployment models [21].

### **2.3.1 Public Cloud**

A public cloud is designed to for use by the general public. A public cloud will typically be owned by a third-party Cloud Service Provider such as Microsoft or Amazon, and will serve lots of different individuals and organisations.

The benefit of a public cloud is that physical infrastructure is completely managed and maintained by the Cloud Service Provider, reducing the effort required to provision computing resources and therefore maximising the benefit of the cloud.

### **2.3.2 Private Cloud**

A private cloud is designed for use by one organisation. This allows individual components of an organisation (such as departments, product groups or engineering teams) to utilise the benefits of Cloud Computing, whilst allowing the organisation to maintain control over the computing resources. A private cloud allows an organisation to completely tailor the cloud to their unique requirements, including specialised hardware, specific Platform/Software as a Service offerings and control over the permissions clients of the cloud environment have.

A private cloud can also be necessary in overcoming concerns about security and data governance. One of the major disadvantages of a public cloud is a lack of control over data (real or perceived). It may not be possible to ascertain where data is geographically located (and therefore what legislation applies to it), and companies may simply not trust confidential information with a third-party Cloud Service Provider.

Whilst a private cloud still requires an organisation to acquire, provision and manage hardware (rather than outsourcing to a third-party Cloud Service Provider), it can still provide a reduction in cost over time. A private cloud allows centralisation of an organisations computing resources, allowing components of the organisation to use resources elastically as required from the central private cloud, rather than duplicating necessary computing infrastructure.

### **2.3.3 Community Cloud**

A community cloud is developed by several organisations that have shared requirements. It allows them to pool together computing resources to the benefit of all organisations involved, reducing the investment needed for a private cloud. Organisations may opt to develop a community cloud to reduce dependency on a public cloud provider, mitigating the privacy and security concerns often cited as being a problem for public clouds, and allowing the resulting cloud system to be tailored to take in to account legislative or administrative restrictions which might be part of some industries or other organisational groups.

Whilst creating a community cloud provides tangible security and customisability benefits over a public cloud, and cost benefits over developing a private cloud system, they also have their issues. Community clouds can make it more difficult to deal with standard distributing computing issues such as latency and resource management, and additional security requirements may be needed [12].

### **2.3.4 Hybrid Cloud**

A hybrid cloud is a composition of 2 other cloud types (public, private and community). Typically, a hybrid cloud uses technology to enable data and applications to be transported between clouds. An example of a hybrid cloud solution would be a private cloud, which utilises a public cloud if it runs out of resources. This allows the private cloud to exhibit the same elasticity benefits of a public cloud, appearing to clients as though it has essentially limitless resources (whilst actually just making use of a public cloud for overflow capacity).

It may be difficult to create a hybrid cloud in some situations as the technologies used may be complete distinct and difficult to combine. There may also be concerns about data security and privacy. Business rules may have to be defined which specify (for example) what types of data can be stored on a public cloud, and what types of data are too sensitive and must remain private at all costs.

## **2.4 Big Data**

The term ‘Big Data’ refers to large scale data sets which present new problems for the processing and analysis of data. These datasets are often too large to be comfortably worked with using standard tools for statistical analysis [27]. Sources of Big Data are diverse; datasets can be from science, industry, social networking sites or various other sources. Consider the following:

- In 2011, Facebook had 30 PetaBytes of data used for performing analytics [34].
- The Large Hadron Collider generates 25 PetaBytes of data annually [33].
- Phase one of the 1000 Genome Project has a dataset of 180 TeraBytes of human genetic information [18].
- In 2008, Google were capable of processing 20 PetaBytes of data a day [16].

### **2.4.1 Challenges**

Big Data introduces several challenges which make the use of traditional analysis tools and techniques infeasible.

#### **2.4.1.1 Scale**

The defining characteristic of Big Data problems is their massive scale. Typical problems may require processing datasets in the magnitude of PetaBytes of information. This makes it unrealistic to process the data in serial, as it would take far too long. Data processing techniques designed for Big Data problems must process information in parallel.

The scale of the data also makes storing data on a single machine unrealistic. Whilst the capacity of hard drives has been increasing over time, the speed of I/O has not increased by the same factor

[32]. This makes it time consuming to read an entire dataset off of one physical disk, even if a disk exists with enough capacity.

Unfortunately, the alternative approach of distributing data across multiple machines also has issues. Using a higher number of nodes increases the likelihood that one of those nodes will fail, which could lead to irrecoverable data loss. In order to prevent this, systems for processing Big Data should be designed to be fault tolerant, usually by introducing redundancy.

#### **2.4.1.2 Predictability**

Not all Big Data is static. There has been increasing interest in performing sentiment analysis on social networks to predict the results of real-world events such as box office revenues [9], financial markets [11], or surveys on political opinion [24].

It can be difficult to predict the quantity of data which may need to be processed when analysing real-time data, such as that gathered by Twitter. In August 2013 Twitter experienced an unexpected increase in traffic, leading to a new record for the number of tweets in a second. This highlights the potentially unpredictable nature of real-time data analytics.

The challenges of predicting resources required for real time data analytics show the advantage of using Cloud Computing for data processing. The elastic nature of clouds would allow resources to be dynamically acquired when an unpredictable increase in data occurs.

#### **2.4.1.3 Data Heterogeneity**

It is very rare for different data sources represent data in the same way. Where data is processed from multiple sources, the lack of standard methods of storing data can make it difficult to develop accurate processing techniques [14].

A lack of structure in data can also cause problems with analysis. Much of the data used in large scale processing is strongly unstructured (social network data, text from articles, etc) which can cause issues with processing techniques. For example a simple data processing task which counts the frequency of words in a text document may produce inaccurate results if there are spelling mistakes in the corpus.

## **2.5 MapReduce**

MapReduce is a programming paradigm designed as a generalised solution to processing large scale datasets [15]. A programmer specifies both a *map* and *reduce* function, a set of input data, and a location for the output. A MapReduce runtime determines how to distribute the task, taking the data and dispersing it amongst its nodes, enabling the data to be processed in parallel.

The key advantage of MapReduce is that it provides an abstraction on top of concurrent programming. This allows a developer to specify what they want to do to the data (in terms of the *map* and *reduce* functions) without having the obscuring the code and having the cognitive overhead of

handling common concurrency issues, such as fault tolerance, data distribution, and safe parallelism without the risk of problems such as race conditions and deadlocks.

The MapReduce method of performing distributed parallel data processing is inspired by the *map* and *reduce* functions present in many functional programming languages [15].

### 2.5.1 Map

The first function that a developer provides is the *map* function.

$$map = (k, v) \rightarrow list(k', v')$$

The *map* function receives a key and a value as input (an *Input Pair*), and returns a list of (different) keys and values (a list of *Output Pairs*). The MapReduce runtime will take all output pairs with the same key, and combine them in to a list before passing the resulting values to the *reduce* function. The reduce function therefore receives an argument of type  $(k, list(v))$ .

### 2.5.2 Reduce

The *reduce* function is the second function provided by the developer.

$$reduce = (k, list(v)) \rightarrow list(v')$$

A *reduce* function merges values together to produce a smaller list of values. Typically, the reduce function is an aggregate function, returning either 1 or 0 results (such as sum, average, etc).

### 2.5.3 Word Counting Example

A common MapReduce operation is word counting. The following pseudo-code implementation of the *map* and *reduce* functions for counting words in a document obtained from [15].

---

**Algorithm 1** Map function for word counting

---

**Require:** key: document name

**Require:** value: document contents

**for all** w in value **do**

    EmitIntermediate(w, 1)

**end for**

---

The *map* function takes a document, and returns a number of Key/Value pairs, where the key is a word appearing in the document, and the value is 1. The runtime environment will then cluster the values together where the keys match. Each word will therefore have a list of 1's, with the length of the list indicating how many times the word has occurred.

---

**Algorithm 2** Reduce function for word counting

---

**Require:** key: a word

**Require:** value: a list of counts

result = 0

**for all** v in values **do**

    result += v

**end for**

**return** result

---

The reduce function takes the list of values (all of which are 1) and sums them together. This gives a total number of times the word has occurred in the document.

### 2.5.4 Disadvantages

The primary criticism of MapReduce is that it provides a limited programming framework [35]. Whilst the MapReduce paradigm is a relatively general concept which applies to many types of application, not all problems can be formulated in a way which is compatible with MapReduce. The MapReduce process consists of a static *map* operation, performed across the data, and a static *reduce* operation performed subsequently. The *map* and *reduce* functions are both stateless.

This imposes limitations on the types of problem which can be solved by MapReduce. If it is not possible to formulate a *map* and *reduce* function for a problem, it cannot be solved by the MapReduce paradigm. Alternatively, whilst it may be possible to express a data processing task in terms of *map* and *reduce*, it does not always provide the most fluent or efficient method of solving the problem.

Prominent examples of this type of algorithm can be found in Machine Learning, where problems are often iterative in nature. Iterative tasks, such as K-Means Clustering can be implemented using the MapReduce paradigm [37], but often require multiple passes of the *map* and *reduce* functions, which causes a significant performance penalty as data must be loaded from the disk every iteration.

### 2.5.5 Hadoop

Hadoop is an Open Source implementation of the MapReduce programming paradigm [4]. It consists of several modules designed to overcome the problems associated with large scale data processing. In addition to the MapReduce programming model (Hadoop MapReduce), the Hadoop platform also has a distributed file system (HDFS) and a resource management and scheduling component (Hadoop YARN).

Hadoop is a particularly popular implementation of the MapReduce interface in the data processing community, emerging as the de-facto standard implementation of MapReduce [25].



## 2.6 PACTs

**Parallelization Contracts (PACTs)** is an alternative programming paradigm which is a generalization of the MapReduce concept [10]. The aim of PACT is to overcome the perceived weaknesses in the MapReduce paradigm, whilst still providing a generic enough framework to represent any data processing task. PACT sets out to improve MapReduce by observing that the *map* and *reduce* functions alone cannot represent all data processing tasks in a natural or efficient way, that MapReduce does not provide flexibility in the order of operations (strictly a *map* followed by a *reduce*) and that MapReduce makes no assumption about the user defined functions, limiting the scope of potential optimizations.

PACT aims to solve these issues in 2 ways. It introduces the concept of Parallelization Contracts, which define properties of a user defined functions input and output data, and it represents the data flow of a data processing job as a Directed Acyclic Graph (DAG), rather than strictly as a *map* and *reduce* task.

### 2.6.1 Processing Tasks

A data processing job can be described as a set of tasks, where each task performs a transformation on the data. A processing task has 3 core components.

A data processing task acts upon a list of records. Unlike the classic MapReduce paradigm, input is not restricted to Key/Value pairs. A record can consist of any number of fields, each which can be either a key or value. All fields must be capable of being serialized and deserialized, and fields defined as keys must be capable of being compared with other keys.

#### 2.6.1.1 Input Contract

A task can be described as consisting of multiple Parallelization Units (PUs). A PU is a core block of computation which must be performed in serial. PUs are isolated from one another, and do not require communication, meaning that they can be distributed across different nodes and can be ran in parallel to one another. PACT specifies a set of Input Contracts which define how a problem is broken down into PUs. The Input Contract is therefore key in determining how the problem is parallelized and distributed between nodes.

The PACT Programming Model provides 5 Input Contracts [5].

- **Map** takes a list of records and creates a PU for each individual record. This allows every record to be processed in parallel. The Map Input Contract is typically used for transforming or filtering data.
- **Reduce** takes a list of records and groups them by record key. It then creates a PU for each group, allowing the resulting subsets to be processed in parallel. The Reduce Input Contract is often used for aggregating data, performing functions like sum or average.

- **Cross** is a multi-input contract, taking 2 lists of records. It takes the Cartesian product of the 2 lists, and creates a PU for each element in the resulting set. This allows every combination of input to be processed in parallel.
- **CoGroup** takes 2 lists of records and groups them by key. A PU is then generated for every resulting group. This is similar to the Reduce Input Contract, but it operates across 2 lists rather than 1.
- **Match/Join** takes 2 lists and matches records from the first with records from the second based on whether they have the same key. A PU is generated for every resulting pair of records. This is conceptually similar to an equi-join operation.

### 2.6.1.2 User Defined Function

The User Function is the programmer defined function which will be executed on the data. This may be counting the frequency of words, searching for a particular string, or various other things. The arguments that the User Function will receive are based on the input contract - if a Map Input Contract is used, the User Function will receive an individual record. If a Reduce Contract is used, the User Function will receive a group of records with similar keys.

### 2.6.1.3 Output Contracts

An Output Contract is an optional component of a data processing task. An Output Contract is used to provide guarantees about the type of data that the user function will return. This allows the PACT runtime to optimise the process to make a more efficient data flow. An Output Contract can indicate that data does not have to be repartitioned between nodes before going on to the next stage data processing task.

There are various Output Contracts.

- **Same-Key** ensures that each record generated by the user defined function has the same key as its input. This ensures that any partitioning between nodes can be kept for the next stage of processing.
- **Super-Key** provides a super-key of the records it was generated from. A function with the Super-Key output contract allows partitioning between nodes to be kept the same.
- **Unique-Key** gives each record a globally unique key across all nodes. This allows records to be stored in data sources which require globally unique keys (e.g. in a relational database table with a primary key).
- **Partitioned-By-Key** partitions records by their key. This has similar implications to the Super-Key contract, in that partitioning is kept, but there is no order within the partitions.

### 2.6.2 Directed Acyclic Graph

Data Processing jobs are represented as Directed Acyclic Graphs [30]. A vertex in the graph represents an individual task (a combination of an input contract, a user defined function, and optionally an output contract). Edges represent the communication between different tasks. Tasks can be connected to multiple other tasks.

The primary advantage of a DAG is that it allows for a more flexible representation of data processing tasks, allowing complex workflows of tasks, rather than being limited to a map task, followed by a reduce task. This allows for arbitrarily complex graphs to be defined, allowing more complex data processing jobs to be completed.

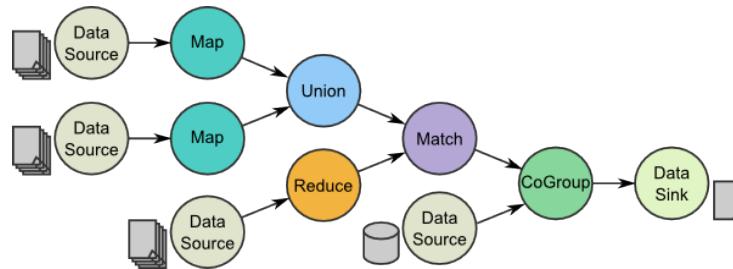


Figure 2.1: An example of a complex dataflow [3]

Directed Acyclic Graphs can also be composed together, by connecting the output of one graph to the input of the next.

The classic MapReduce paradigm could be emulated by having 2 tasks, one with the Map Input Contract and another with the Reduce Input Contract (neither would have Output Contracts). The result of the Map task would be piped directly in to the Reduce task.

### 2.6.3 Nephele

Nephele is the reference implementation of the PACT programming model. It is a runtime environment which takes a Directed Acyclic Graph specifying the desired data processing workflow (the Job Graph) and compiles it in to an Execution Graph - a more concrete description with information about how the tasks will be parallelized and what types of computing resources will be used [31].

A secondary focus of the Nephele runtime is to take advantage of the opportunities afforded by Cloud Computing. The core benefit of Cloud Computing is elasticity, allowing resources to be obtained on demand. By removing the assumption that resources must be static throughout the duration of a data processing job, Nephele is able to utilise the dynamic resource allocation made possible by the cloud. This changes the emphasis of task scheduling, allowing the scheduler to determine and acquire what resources a given task needs, rather than attempting to schedule tasks depending on the resources available at the time [31].

## **Chapter 3**

# **Current Progress**

### **3.1 General Progress**

As indicated in the schedule, the mid-year report is a key milestone in the project. To date I have completed the Aims & Objectives section of the report, laying out what I hope to achieve in the project, and why it is relevant. I have also completed the necessary Background Research for the project, discussing Cloud Computing and Big Data, key concepts of my project, and the technologies that I am going to be assessing in my experiments.

I have initial ideas for the design of my experiments which are outlined below. I have also made progress with the technologies which will be required for implementation and

Outside of the report, I have presented my project to the Distributed Systems and Services research group, outlying the idea for my project, the core questions I hope to answer and how I plan to achieve answers to those questions. The presentation was received well, and feedback was positive.

I am currently on track according to my project schedule.

### **3.2 Experiment Design**

I plan to run a series of experiments to test Hadoop and Nephele, with the aim of answering my research questions. There will be a total of 18 experiments, with 3 factors being varied to test the tools in a range of scenarios to answer the research questions.

#### **3.2.1 The Data Processing Tool**

The first factor that will be varied is the data processing tool. Experiments will be run in 3 tool configurations.

### **3.2.1.1 Hadoop**

Hadoop is the established tool for performing large scale data processing. It therefore acts as a reference point for acceptable levels of efficiency in data processing, and allows comparison to a real-world tool.

Hadoop can also be considered as the reference implementation of the MapReduce programming paradigm. This makes it an ideal choice for the comparison of MapReduce to PACT.

### **3.2.1.2 Nephele using MapReduce**

Experiments will be run using Nephele, but limiting the operations available to the MapReduce subset. This allows Nephele and Hadoop to be directly compared, as they can both process tasks using MapReduce. If Nephele can perform MapReduce tasks more efficiently than Hadoop, there may be limited value to the existing established system.

### **3.2.1.3 Nephele using PACT**

Nephele is a tool which implements the PACT programming paradigm, which as a superset of MapReduce can also perform tasks in a MapReduce style. This means that experiments can be implemented using the same tool, but in different programming paradigms, allowing a fair test of PACT vs Nephele. This is designed to answer the first research question, namely whether or not PACT overcomes the inherent disadvantages of the MapReduce paradigm.

In a broader sense, it allows a complete comparison of Hadoop and Nephele. In real-world data processing scenarios, users of Nephele would be unlikely to restrict their programming options to just MapReduce, and would be likely to use other aspects of PACT as appropriate. Running experiments in the same way allows a fairer comparison of the 2 tools, where all of their functionality is available.

## **3.2.2 The Problem**

Data Processing Tools are generic and can solve a wide range of problems. I plan to use the tools to solve 3 different problems, each designed to test the tools in different scenarios.

The specific problems and datasets are yet to be decided, although potential problems are listed for each type.

### **3.2.2.1 A ‘Classic’ MapReduce problem**

There are various problems which naturally fit to the MapReduce paradigm, and have been implemented several times to benchmark Hadoop and other MapReduce tools. The classic MapReduce problem will give a good representation of how well Nephele can perform MapReduce tasks in comparison to Hadoop.

One issue with choosing a classic MapReduce problem is that PACT does not necessarily add anything to the solution of the problem. Depending on the choice of problem, it could be reformulated to use some of the other input contracts that PACT provides. Alternatively, even if only the Map and Reduce input contracts are used, PACT output contracts could be used to potentially improve performance.

Examples of Classic MapReduce problems are word counting, a distributed text search ('grep') or Terasort.

### **3.2.2.2 A Non-Classic MapReduce problem**

It is well documented that there are various problems which are difficult to reformulate into the MapReduce paradigm. This is often cited as one of the major disadvantages of MapReduce. As these problems still need to be solved in Big Data situations, a sub-optimal use of the MapReduce paradigm is often used. This provides an opportunity to test whether the extra flexibility of the PACT programming model translates into actual benefits, and whether it overcomes the disadvantages of MapReduce.

Problems that MapReduce are not suited to are typically iterative in nature, such as K-Means clustering.

### **3.2.2.3 A Real-World Problem**

Whilst there is value in testing simple problems such as word counting for benchmarks, they are artificial and may not provide a reflection of how data processing tools are used in industry and academia. A real world problem will be used to determine how well the data processing tools perform in a more realistic scenario. As a real world scenario is likely to be more complex, it provides more of an opportunity to take advantage of different aspects of the data processing software. There is rarely one 'correct' way of solving a non-trivial problem, and there will therefore hopefully be ways of solving the problem which allow for PACT and MapReduce solutions developed in an idiomatic way.

Various data sets are made publicly available. Amazon make 55 large datasets publicly available for analysis [7], including data from the 1000 Genomes Project (a map of human genetic variation), the NASA NEX project (various scientific datasets, including images of the Earth's surface and climate change projections) and US Census data.

As an alternative, the School of Computing has a 40GB dataset with information on Google data centres.

I hope to find papers demonstrating existing scientific analysis on a publicly available dataset (possibly performed by methods such as MapReduce). I will then attempt to replicate the results of the analysis using my chosen data processing tools.

### **3.2.3 Deployment Environment**

The final research question is how well the data processing tools perform in Cloud Computing environments. Hadoop is ‘rack-aware’ - the machines used in a data processing task must be known up front, and cannot change throughout the process. One of the stated research goals of Nephele is to take maximum advantage of the elasticity that Cloud Computing affords.

In order to assess the performance of both tools in Cloud Computing environments, I will execute the experiments in 2 different environments.

#### **3.2.3.1 Cloud Testbed**

The experiments will all be run on the School of Computing cloud testbed, a private cloud operated by the Distributed Systems and Services group. This provides a static environment with well known hardware and limited elasticity.

#### **3.2.3.2 Public Cloud**

The experiments will also be run on a public cloud, such as those provided by Amazon or Microsoft. In a public cloud environment, the hardware is not known and could be of varying quality. This will show whether designing Nephele to run on the cloud, and to take advantage of the elasticity and available resources, translates in to real world benefits.

## **3.3 Experiment Implementation**

Experiments will be implemented using the Scala programming language [1]. Scala has been chosen for the following reasons.

- All experiments should be implemented in the same programming language to maximise code reuse, and allow for easier comparison of implementations.
- Nephele has limited support for programming languages, whereas Hadoop (as a more mature project) supports many more. Nephele currently only supports Java and Scala [2]. The Scala API for Nephele currently has superior documentation.
- Code examples illustrating Hadoop and Nephele tasks are substantially terser than the Java equivalents.

I have implemented common introductory Hadoop exercises using Scala and have executed them on a local emulator. These basic implementations use an Open Source Hadoop library provided by Twitter (called Scalding) [28].

I have received access to the School of Computing Cloud Testbed, and have carried out introductory exercises on provisioning Virtual Machines. There are currently some issues with the Hadoop

Virtual Machine, but I hope these will be resolved in the near future so I can run tests in the environment the experiments will be executed in.

## 3.4 Evaluation

I plan to evaluate the project on a number of factors.

### 3.4.1 Technical Evaluation

The technical evaluation will evaluate the results of the experiment, and determine what the results of the experiment mean. The aim of the technical evaluation will be to answer the research questions. Key to this is the definition of efficiency which is used to evaluate the tools. There are a number of types of efficiency which could be used to evaluate the project.

The tools will primarily be evaluated on Runtime Efficiency, though there are various alternative metrics which could be used.

- **Runtime Efficiency** Runtime efficiency is the length of time that it takes to complete a data processing job. In order to determine runtime, each experiment will be run multiple times with each individual runtime being averaged. This will minimise discrepancies caused by hardware, over-utilisation of resources, etc.

The runtime efficiency is an important factor because completing data processing tasks in a timely manner is one of the largest considerations in Big Data scenarios. This will form the bulk of the technical evaluation into how efficient the tools are.

- **Resource Utilisation** The tools should use resources in the best possible way. If a data processing tool is only using half of the possible resources available to it on a virtual machine, it may explain why it is less efficient (in regards to runtime) than an alternative tool. Likewise, excessive use of disk I/O may lead to a slower solution.
- **Scalability** It is essential to use distributed computing to process large amounts of data. An important consideration in this environment would be how adding extra machines improves the runtime efficiency of a solution. If one tool scales much better than an alternative, it may be a more suitable choice for big data situations, even if the alternative has a better runtime efficiency when a small number of machines are used.
- **Cost** One of the major factors of Cloud Computing is cost. Resources are charged on a pay-per-usage model, so the more resources that are allocated for data processing, the higher the cost will be. An evaluation can be performed of the cost of resources in comparison to the amount of work completed.

An evaluation of cost would take in to account the cost of cloud computing compute time to the amount of time it takes to complete a task. Cloud Service Providers such as Microsoft



and Amazon offer hosted Hadoop platforms (as a Platform as a Service offering), and the cost of this could be compared to performing data processing tasks on Infrastructure as a Service offerings (creating a set of virtual machines with Hadoop). The scalability of a data processing tool will be relevant to the cost (at what point does it become more expensive to add new virtual machines than the benefit it provides?). The cost of using the cloud could also be compared to the relative cost of purchasing hardware and setting up a private cloud (or merely creating a static data processing data centre).

### **3.4.2 Process Evaluation**

The process evaluation will evaluate the process of the project as a whole, rather than considering the results of the experiments. The process will also be evaluated through a number of factors.

- Does the technical evaluation match the hypothesis?
- Have the research questions been answered?
- Does the work contribute to the existing research landscape?
- Is there any further scope for research in this area?

# Bibliography

- [1] The scala programming language, 2014.
- [2] Stratosphere programming guides, 2014.
- [3] Stratosphere programming model, 2014.
- [4] Welcome to apache hadoop!, 2014.
- [5] Alexander Alexandrov, Max Heimel, Volker Markl, Dominic Battré, Fabian Hueske, Erik Nijkamp, Stephan Ewen, Odej Kao, and Daniel Warneke. Massively parallel data analysis with pacts on nephele. *Proceedings of the VLDB Endowment*, 3(1-2):1625–1628, 2010.
- [6] Amazon. Aws — amazon elastic compute cloud (ec2) - scalable cloud services, 2014.
- [7] Amazon. Public data sets on aws, 2014.
- [8] Alex Amies, Harm Sluimen, Qiang Guo Tong, and Guo Ning Liu. *Developing and Hosting Applications on the Cloud*. IBM Press/Pearson, 2012.
- [9] Sitaram Asur and Bernardo A Huberman. Predicting the future with social media. In *Web Intelligence and Intelligent Agent Technology (WI-IAT), 2010 IEEE/WIC/ACM International Conference on*, volume 1, pages 492–499. IEEE, 2010.
- [10] Dominic Battré, Stephan Ewen, Fabian Hueske, Odej Kao, Volker Markl, and Daniel Warneke. Nephele/PACTs: A programming model and execution framework for web-scale analytical processing. In *Proceedings of the 1st ACM symposium on Cloud computing, SoCC '10*, pages 119–130, New York, NY, USA, 2010. ACM.
- [11] Johan Bollen, Huina Mao, and Xiaojun Zeng. Twitter mood predicts the stock market. *Journal of Computational Science*, 2(1):1–8, 2011.
- [12] Gerard Briscoe and Alexandros Marinos. Digital ecosystems in the clouds: towards community cloud computing. In *Digital Ecosystems and Technologies, 2009. DEST'09. 3rd IEEE International Conference on*, pages 103–108. IEEE, 2009.

- [13] Rajkumar Buyya, Chee Shin Yeo, and Srikumar Venugopal. Market-oriented cloud computing: Vision, hype, and reality for delivering it services as computing utilities. In *High Performance Computing and Communications, 2008. HPCC'08. 10th IEEE International Conference on*, pages 5–13. Ieee, 2008.
- [14] Alfredo Cuzzocrea, Il-Yeol Song, and Karen C Davis. Analytics over large-scale multidimensional data: the big data revolution! In *Proceedings of the ACM 14th international workshop on Data Warehousing and OLAP*, pages 101–104. ACM, 2011.
- [15] Jeffrey Dean and Sanjay Ghemawat. Mapreduce: Simplified data processing on large clusters. In *OSDI*, pages 137–150. USENIX Association, 2004.
- [16] Jeffrey Dean and Sanjay Ghemawat. Mapreduce: simplified data processing on large clusters. *Communications of the ACM*, 51(1):107–113, 2008.
- [17] Ian Foster, Yong Zhao, Ioan Raicu, and Shiyong Lu. Cloud computing and grid computing 360-degree compared. In *Grid Computing Environments Workshop, 2008. GCE'08*, pages 1–10. Ieee, 2008.
- [18] National Human Genome Research Institute. The 1000 genomes project more than doubles catalog of human genetic variation, October 2012.
- [19] Platform as a service (paas) drives cloud demand. Technical report, Intel, August 2013.
- [20] L. Kleinrock. UCLA to be first station in nationwide computer network. UCLA Press Release, July 1969.
- [21] Peter Mell and Timothy Grance. The nist definition of cloud computing. 2011.
- [22] Microsoft. Pricing calculator — windows azure, 2014.
- [23] Microsoft. Windows azure, 2014.
- [24] Brendan O'Connor, Ramnath Balasubramanyan, Bryan R Routledge, and Noah A Smith. From tweets to polls: Linking text sentiment to public opinion time series. *ICWSM*, 11:122–129, 2010.
- [25] Xiongpai Qin, Biao Qin, Xiaoyong Du, and Shan Wang. Reflection on the popularity of mapreduce and observation of its position in a unified big data platform. In *Web-Age Information Management*, pages 339–347. Springer, 2013.
- [26] salesforce. Salesforce crm, 2014.
- [27] Chris Snijders, Uwe Matzat, and Ulf-Dietrich Reips. "big data": Big gaps of knowledge in the field of internet science. *International Journal of Internet Science*, 7(1), 2012.
- [28] Twitter. twitter/scalding, 2014.

- [29] Luis M Vaquero, Luis Roderio-Merino, Juan Caceres, and Maik Lindner. A break in the clouds: towards a cloud definition. *ACM SIGCOMM Computer Communication Review*, 39(1):50–55, 2008.
- [30] Daniel Warneke and Odej Kao. Nephele: efficient parallel data processing in the cloud. In *Proceedings of the 2nd workshop on many-task computing on grids and supercomputers*, page 8. ACM, 2009.
- [31] Daniel Warneke and Odej Kao. Exploiting dynamic resource allocation for efficient parallel data processing in the cloud. *Parallel and Distributed Systems, IEEE Transactions on*, 22(6):985–997, 2011.
- [32] Tom White. *Hadoop: The Definitive Guide: The Definitive Guide*. O’Reilly Media, 2009.
- [33] WLCG. Welcome to the worldwide lhc computing grid — wlcg.
- [34] Paul Yang. Moving an elephant: Large scale hadoop data migration at facebook, 2011.
- [35] Matei Zaharia, Mosharaf Chowdhury, Michael J Franklin, Scott Shenker, and Ion Stoica. Spark: cluster computing with working sets. In *Proceedings of the 2nd USENIX conference on Hot topics in cloud computing*, pages 10–10, 2010.
- [36] Qi Zhang, Lu Cheng, and Raouf Boutaba. Cloud computing: state-of-the-art and research challenges. *Journal of internet services and applications*, 1(1):7–18, 2010.
- [37] Weizhong Zhao, Huifang Ma, and Qing He. Parallel k-means clustering based on mapreduce. In *Cloud Computing*, pages 674–679. Springer, 2009.

## **Appendix A**

### **Potential Ethical Issues**

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Ethical issues may occur depending on the data used for the experiments. A variety of different datasets are available which could be used for the ‘real-world’ experiment. Data may contain personally identifiable information, or have other ethical concerns.

It can be assumed that any dataset used will be publicly available, and will be suitably anonymised with suitable stakeholders having been consulted. For example, the 1000 Genomes project will contain the genome information of a large number of people. It can be assumed that those people have agreed to make their genome data available for research purposes.

There may be no ethical concerns, depending on the dataset selected.