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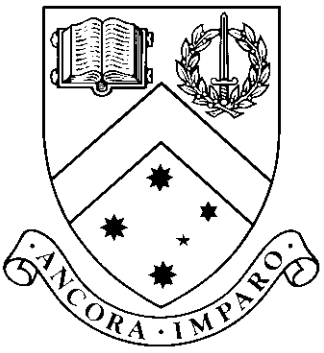

Honours Research Proposal — Semester 2, 2014

A pipeline for the preprocessing and storage of heterogeneous big data [WORKING TITLE]

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Contents

1 Introduction

Currently, as a society, we are generating very large amounts of data from a large range of different sources. These sources include scientific experiments, such as the Australian Synchrotron [5] and The Large Hadron Collider [7], companies, such as Amazon [2], and also data generated by end users of products, such as social networks. The rate of data that is being generated is constantly increasing, presenting major challenges when it comes to the storage and processing of that data [11]. This is what is often referred to as "Big Data". Out of all of this data we are faced with, often only specific parts of the data are of use for given purposes. Hence rather than attempting to store all the new data that is being generating, often what is done, in both academia and industry associated with big data, is the realtime processing and analysis of incoming data streams.

There are currently numerous realtime data processing frameworks that are in development and in production use, both in industry and academia. Examples of these realtime data processing frameworks include the widely used Storm project [1] developed at BackType and Twitter, Inc., and also the up-and-coming Spark Streaming project [9] developed at UC Berkeley's AMPLab [3], both of which are open- source projects. While there are a growing number of these projects being developed, often these projects are designed with a particular type of data in mind, or to facilitate a particular type of data processing. For example, the before mentioned Spark Streaming project, along with its mother project, Spark [4], was designed for highly parallelised data with the use-case in mind of processing data in-memory using highly iterative machine learning algorithms related to data analytics [19].

Given these, occasionally "narrow", use-cases for existing data stream processing frameworks, challenges are faced in supporting the variations in both data types and processing requirements for data processing applications. In this research project, we aim to study the different characteristics of the data processing requirements based on the different characteristics of the data types. The knowledge found of these characteristics will be compared with the properties of existing solutions for big data processing.

What we propose in this document is an entire heterogeneous data processing pipeline that will facilitate the following tasks, in sequence:

1. Take in streams of data from various sources.
2. Aggregate similar types of data.
3. Process the data appropriately, depending on its type and the application.
4. Store the results of the data processing on an appropriate storage medium.

From this research project, we aim to produce a set of recommendations on choosing the various components of the pipeline, along with recommendations on how the components should be interconnected. To complement this, we also aim to produce a design template on the deployment of the pipeline in a cloud environment. This will be expanded on in further detail in §6.

This document will be structured as follows:
Discussion of the existing research and work done into this area will be touched on in §2. Our research questions, along with an outline of what we will be doing will be outlined in §3. The methodology used to achieve the deliverables of this project will be discussed in §4. The design of the entire research project will be shown in §5. Finally, we will conclude with an overview, in §6, of what the expected outcomes and deliverables of this project will be.

2 Research Context

2.1 Big data

Big data, as explained previously, is becoming commonplace in both industry and academia. Everyday companies are finding that they are generating too much data and that their traditional database management system (DMBS) solutions cannot scale to the epic proportions needed to handle this data in an efficient and robust manner [20]. Hence, companies and academics alike have started looking at alternative solutions designed with the goal of handling these massive datasets.

The most popular solution for this problem, up until recently, has been the MapReduce model of programming along with some type of scalable distributed storage system [10]. The MapReduce model was started at Google, Inc. with their own proprietary implementation along with their proprietary distributed file system, known as the Google File System (GFS). Without going into the low-level details of MapReduce and GFS, the use of this solution at Google allowed the company to easily handle all the data that was coming into their servers, and perform the necessary processing operations that was needed at the time [14] [12].

2.2 Apache Hadoop

From the success of MapReduce usage combined with GFS at Google, the open-source community responded swiftly with the development of the Apache Hadoop framework. Hadoop originally offered an open-source implementation of MapReduce and their own open-source distributed file system known as the Hadoop Distributed File System (HDFS) [22].

Hadoop soon became the subject of mass-adoption in both industry and academia, being deployed at a fast rate. Development of the Hadoop framework also grew at a fast rate, with new applications related to HDFS and MapReduce being built on top of Hadoop, greatly benefiting the ecosystem as a whole. Some of these applications grew into widely adopted systems in their own right. For example, Hadoop applications such as Apache Pig [13] and Hive [24] allow for easy querying and manipulation of data stored on HDFS, both coming with the addition of their own "SQL-like" query languages [21].

Additionally, as further non-MapReduce model applications became of interest to the Hadoop community, Hadoop soon developed a further abstraction on top of the underlying resources (in most cases, HDFS). The goal of this was to facilitate the development and deployment of many different applications, varying in use-case, which could be run on the Hadoop ecosystem, without forcing developers to fit their application into the MapReduce model. This development was known as Apache Hadoop YARN: Yet Another Resource Negotiator, which can be thought of as an operating system sitting atop of the available Hadoop resources [26]. The abstraction YARN provides facilitated the development of much more advanced, and non-MapReduce technologies which have since become widely used parts of the Hadoop ecosystem [15].

2.3 Realtime data processing

One of the major limitations of Hadoop, and the MapReduce model in general, soon became obvious: MapReduce was designed with the goal of being able to process batches of data, hence, given Hadoop's dominance, batched data processing was the focal point of the entire distributed data processing domain [17]. Essentially, batched data processing is where data gets collected first into large enough batches before being processed all-at-once. The point of processing in such a way is so there would be less overheads than attempting to process each individual datum as it arrives. For a lot of use-cases this was, and still is, fine as there were no other drawbacks apart from a high level of latency

between the stages of when the data arrives and when it gets processed. However, for other applications, such as stock trading, sensor monitoring, and web traffic processing, a more low-latency, realtime solution was needed [17].

Soon, many solutions, with different use-cases and design goals, were developed in the area of distributed stream processing systems (DSPS). Given the Hadoop ecosystem that was already widely adopted, most of these DSPSs were built upon the still new YARN layer, ensuring overall compatibility with the Hadoop ecosystem, and the underlying HDFS. Some examples of such projects include the beforementioned Apache Storm, currently being used at Twitter, Inc. [25], among many other companies. Also up-and-coming projects, such as Apache Samza which is a recently open-sourced project, currently being used in production at LinkedIn Corporation [8].

2.4 The future

While the overall area of big data processing has definitely been moving at a very fast pace in the last decade, the area focused on realtime big data processing is still relatively young and shows much potential for further growth in the way of research. As of writing, there are a considerable amount DSPS technologies available and in active development, and are fast gaining adoption in industry.

While the various DSPS technologies available offer much needed realtime data stream processing functionality, it is rather confusing for the end-user to differentiate between which of the technologies would be best given the users' specific use-case and the class of data they are working with.

Currently, real time data stream processing is presented in most of the major DSPS technologies as a collection of steps. For example, Apache Storm's processing topologies are made up of the "bolt" processing step abstraction along with Apache Samza's processing model being made up of their "task" abstractions [17]. Hence, with the existence of various DSPS technologies within the Hadoop ecosystem and elsewhere, and the idea of data stream processing as a collection of processing steps, the DSPS components can be set up in a pipeline topology for general data processing. The idea behind this pipeline being that each step along the way in the pipeline can be made up of loosely related DSPS technologies, depending on the class of data needed to be processed. There is no fixed pipeline; the general model should be DSPS-agnostic.

There has recently been an attempt at introducing a DSPS-agnostic architecture, known as the Lambda architecture [20], that is currently gaining traction in the academic community [16] [19].

We propose looking into the Lambda architecture, and similar attempts, as inspirations for our research project that will produce a set of processing recommendations for given data classes and, from those recommendations, the dynamic construction of a heterogeneous data processing pipeline.

3 Objectives

3.1 Research questions

The following research questions will be the main focus of our project:

1. What characteristics of data systems can be identified to develop a data class taxonomy for real time big data processing?

2. How can the taxonomy, stated in (1), be utilised to provide a set of recommendations in designing a pipeline of data processing components to support a particular data system's processing requirements?

3. How can the recommendations be used in practice to modify existing data pipelines when requirements change?

Additionally, after answering each of these preliminary research questions, we will want to properly implement the theoretical discoveries from each stage. We do this with the goal of achieving some deployable pipeline that can be then be used in the testing and overall evaluation stages.

Note that the methodology behind how we are going to answer these questions is given in §4.

3.2 Research aims

The main aim or goal of this research project is to develop a set of recommendations that define exactly how certain types, or classes, of data should be processed. These recommendations can then be used to specify particular DSPS technology that can be used to make up a realtime data processing pipeline. The purpose of the pipeline being to take data from arbitrary sources, process it in some specified way, then store the needed results on some storage medium, *e.g.* HDFS.

Relating back to the first research question, to achieve the goal of developing a set of processing recommendations for specific classes of data, we first aim to discover and implement a classification model for the purpose of classifying different types of data. To implement the entire pipeline, this classification stage will need to happen early on, hence will be one of our first aims we attempt to satisfy.

By the end of the project, we aim to have a proof-of-concept implementation of the pipeline working on the National eResearch Collaboration Tools and Resources (NeCTAR) cloud [6]. Further details regarding NeCTAR can be found in §4.1 and §5.4. Further details can be found on the implementation of the pipeline in §6.

We aim to be able to automate the formulation of some NeCTAR-compatible scripts, based on the data processing recommendations. These scripts will be generated with the aim of enabling NeCTAR end-users to be able to deploy a specific variation of the pipeline on their NeCTAR instances. The scripts, and the pipelines they produce, will vary in which DSPS technologies make up the pipeline for the given use-case. The use-case being for the specific class of data that they are attempting to process.

Further detail on the project deliverables based upon these aims can be found in §6.

4 Methodology

4.1 Use of NeCTAR cloud services

One of the key parts of our research methodology will be the applied use of the National eResearch Collaboration Tools and Resources cloud (NeCTAR) [6]. Access to this cloud will facilitate the majority of applied work that happens in this project, including the testing of existing big data stream processing technologies along with the evaluation of our project's technical outcomes. It will also serve as the target platform for the implementation and deployment of our pipeline.

To give a brief overview of NeCTAR, NeCTAR is a $47 million (AUD) project funded by the Australian government to facilitate Australian eResearch through providing shared Cloud infrastructures, among other facilities [23].

As of writing, we have requested two NeCTAR Cloud instances for this project's use. The instances having 16 shared cores, 6400 hours of processing time, and one terabyte of shared volume storage. Going by initial estimates, these requested resources should suffice for the scope of this research project. These resources are further touched on in §5.4.

4.2 Data classification method

For the research methodology surrounding the data classification method, we will employ a qualitative classification method with the aim of producing a taxonomy of the different classes of data. This will allow us to clearly show the requirements needed for processing each of the specific classes of data. Similarly, producing a taxonomy for a range of different open-source DSPS technologies will allow us to show the data requirements for each specific DSPS. The purpose of this taxonomy of DSPS technologies being so that we can directly form recommendations for the processing of specific classes of data, relating such data classes with specific DSPS technologies that would be best suited for the given task.

From preliminary research for this project, we have discovered that there is a rather small set of possible DSPS technologies currently available to choose from. Hence, regardless of the number of different classes of data, multiple different classes may have to be given the same DSPS recommendations, effectively limiting the number of data classes. This makes the task of employing a data classification method much more simple in the context of this project.

4.3 Data processing recommendations

As stated in (2), in §3.1, we will formulate specific processing recommendations for each given class of data. An example of these recommendations would be for data displaying properties such as those of belonging to a graph data class. For this data class, we would recommend the usage of the GraphX abstraction on top of the Apache Spark DSPS for processing, given GraphX's suitability for the processing of graph data [27].

These recommendations will be based directly off the data class and DSPS taxonomies that we will produce, as discussed in §4.2.

5 Research Design

5.1 Proposed thesis chapter headings

The proposed structure of the thesis is as follows:

1. Introduction
    1.1. Overview
    1.2. Background
    1.3. Research problem
    1.4. Research questions
    1.5. Research scope
    1.6. Conclusion and thesis structure
2. Literature Review
    2.1. Introduction
    2.2. Definition of terms
    2.3. Big data in industry and academia
    2.4. Batch data processing
    2.5. Overview of Hadoop ecosystem
    2.6. Realtime data processing
    2.7. Overview of realtime data processing technologies
    2.8. Disruptive research in big data
    2.9. Conclusion
3. Streaming Data Preprocessing Pipeline Model
    3.1. Introduction
    3.2. Taxonomy of streaming data systems
    3.3. Application of taxonomy to build set of recommendations
    3.4. Composing recommendations into pipeline
    3.5. Overview of pipeline
    3.6. Usage of pipeline
    3.7. Conclusion
4. Implementation
    4.1. Introduction
    4.2. Implementation environment
    4.3. Use cases for implementation
    4.4. Data processing technologies for pipeline
    4.5. Implementation of pipeline in NeCTAR cloud
    4.6. Conclusion
5. Discussion and Evaluation
    5.1. Introduction

5.2. Performance evaluation

5.3. Discussion

5.4. Conclusion

6. Conclusion

6.1. Overview

6.2. Research contributions

6.3. Research limitations

6.4. Future research

7. Reference List

8. Appendices

5.2 Timeline

The following is a preliminary estimated timeline of the proposed research project:

Task / Deliverable	**Deadline**
First meeting with supervisors	2014-07-29
Scoping finalised	2014-08-11
Research proposal draft submission	2014-09-01
Research proposal final submission	2014-09-05
Preliminary research complete	2014-10-16
Literature review draft submission	2014-10-31
Interim presentation	2014-11-03
Literature review final submission	2014-11-07
Qualitative comparisons complete	2014-12-07
Data classification method complete	2015-01-01
Data processing recommendations due	2015-01-28
NeCTAR script implementation due	2015-02-28
Testing of pipeline on NeCTAR	2015-03-15
Evaluation of pipeline system	2015-04-01
Thesis draft submission	2015-05-29
Final presentation	2015-06-08
Thesis final submission	2015-06-19

Note that the above is simply a proposed timeline, and it is highly probable that this will be subject to change as the project progresses.

5.3 Potential difficulties

While we believe that most components of this project are very much feasible given the time and resources we have been allocated so far, we have identified a small number of possible difficulties that may be encountered as the project progresses. The most obvious difficulty so far that we have identified is the need to acquire a substantial amount of data that we can use for both during the testing and the evaluation stages of the project. As this data will be used to test our data classification methods and evaluate our pipeline deployed in the cloud, it will need to be diverse. By diverse, what we mean is it must display heterogeneity in terms of its type and origin; data from many different sources would be ideal.

Currently we have no concrete leads on the acquisition of this data, although we will look into collaboration with other data-based research projects ongoing at Monash University. We also are yet to explore freely available data sets, such as the Enron corpus email dataset [18], although these may definitely be taken into consideration at a later stage in the project in the case that data acquisition proves infeasible.

5.4 Special facilities required

As we are aiming to deploy a proof-of-concept of this pipeline, the main special facility needed access to is a cloud solution that enables us to install and test our pipeline. For this, we have already requested access for what we are planning to do in this project on the National eResearch Collaboration Tools and Resources (NeCTAR) cloud [6]. This cloud is funded by the Australian Government and available to Australian researchers in many different disciplines.

With access to this cloud for the duration of this project, we will be able to install and perform qualitative comparisons between the numerous realtime data processing solutions available as of now. This will assist us in making our recommendations for the pipeline based on the classification of particular set of data.

This access to cloud resources at NeCTAR will also facilitate our later testing and evaluation stages of the project, where we will be hoping to test the pipeline with real heterogeneous data.

6 Expected Outcomes

The expected outcomes of this project include both technical contributions and theoretical contributions; the technical outcomes of the project essentially being implementations of the theoretical outcomes.

Our main theoretical contribution will be the realtime processing recommendations we produce for specific classes of data. These recommendations will recommend specific realtime data processing technologies for use within the pipeline to process the given data.

Looking at the project's outcomes in terms of technical contributions, they directly relate back to the theoretical contributions. The main technical contribution will be NeCTAR template scripts which enable the deployment of the pipeline on the NeCTAR cloud. These scripts will be constructed based upon the recommendations produced for specific dataset classes.

To summarise, the expected outcomes of this project include the following contributions:

- Recommendations for specific classes of data on how they should be processed in realtime.
- NeCTAR compatible scripts allowing NeCTAR users to deploy the recommended pipelines on the NeCTAR cloud.

All of these contributions will hopefully be assembled together to make a complete pipeline generating system for any arbitrary type of data.

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