Universidad de Granada / Instituto de Astrofísica de Andalucía

BigData. Integrating NoSQL Technologies into Virtual Observatory

Máster en Métodos y Técnicas Avanzadas en Física

Trabajo Fin de Máster presentado por José Antonio Magro Cortés

2013

Contents

List of Figures

List of Tables

Chapter 1

Overview

The volume of data produced at some science centers presents a considerable processing challenge. At CERN, for instance, several hundred million times per second, particles collide inside LHC. Each collision generates particles that often decay in complex ways into more particles. The pass of particles are recorded through a detector that sends the data for digital reconstruction. Physicists have then to browse through petabytes of data annually yielded to determine if the collisions have thrown up any interesting information.

CERN, like many other science centers, does not have the computing or financial resources to manage all of the data on its site, so it moved into the grid to share the load with computing centers around the world. The Worldwide LHC Computing Grid is a distributed system which gives over 8000 physicists near real-time access to LHC data.

So we could think that current deployed technologies are maybe obsolete and a new rethink should be made. If CERN (but not just CERN as we will discuss later) has changed its storage policy (leaving behind the classic client-server model), why not change the way the data are accessed?

Almost a decade after E. Codd published his famous relational model paper, the relational database management systems (RDBMS) have been the *de facto* tools.

Today, non-relational, cloud, or the so-called NoSQL databases are growing rapidly as an alternative model for database management. Often more features apply such as schema-less, easy replication feature, simple API, eventually consistent / BASE (not ACID), a huge amount of data (big data) and more.

In this work, we give a short overview of big data problem and present an alternative, using one of the NoSQL databases (today, the volumes of data that can be handled by NoSQL systems exceed what can be handled by the biggest RDBMS) freely available, to offer a different way of challenging some of these problems, always operating inside VO frame.

Chapter 2

Astronomy Big Data

Big data are high-volume, high-velocity, and/or high-variety information assets that require new forms of processing to enable enhanced decision making, insight discovery and process optimization. Examples of big data include information such as Web search results, electronic messages (e.g. SMS, email and instant messages), social media postings, pictures, videos and even system log data. However, it can also include cash transactions, check images, receipts and other transactional information depending on the source of the information. This situation requires processing of terabytes and even petabytes of data. This is achieved by distributed processing. This is one of major reasons for the power of Web companies such as Google, Amazon or social networks like Facebook and Twitter. Relational databases are found to be inadequate in distributed processing involving very large number of servers and handling Big Data applications.

Astronomical datasets are growing at an exponential rate: the next generation of telescopes will collect data at rates in terabytes per day. This data deluge, now and int the future, presents some critical challenges for the way astronomers get new knowledge from their data.

In this chapter, we make an overview of some of the greatest telescopes and the amount of data they acquire and store.

2.1 Atacama Large Millimiter Array

ALMA is a worldwide project; the synthesis of early visions of astronomers in its three partner communities: Europe, North America and Japan. It is a fusion of ideas, with its roots in three astronomical projects: the Millimeter Array (MMA) of the United States, the Large Southern Array (LSA) of Europe, and the Large Millimeter Array (LMA) of Japan.

Figure 2.1: ALMA dishes in Atacama Desert

ALMA is an instrument that consists of a giant array of 12-m antennas with baselines up to 16 km, and an additional compact array of 7-m and 12-m antennas to greatly enhance ALMA's ability to image extended targets, located on the Chajnantor plateau at 5000m altitude. Initially, it will observe at wavelengths in the range $3mm$ to $400m$ (84 to $720GHz$). The antennas can be moved around, in order to form arrays with different distributions of baseline lengths. More extended arrays will give high spatial resolution, more compact arrays give better sensitivity for extended sources. In addition to the array of 12-m antennas, there is the Atacama Compact Array (ACA), used to image large scale structures that are not well sampled

by the ALMA 12-m array, consisting of twelve 7-m antennas and four 12-m antennas.

The design of ALMA is driven by three key science goals:

- Detecting spectral line emission from CO in a normal galaxy like the Milky Way at a redshift of $z = 3$, in less than 24 hours.
- Imaging the gas kinematics in protostars and in protoplanetary disks around young Sun-like stars in the nearest molecular clouds ($150pc$).
- Providing precise high dynamic range images at an angular resolution of $0.1arcsec$

The current ALMA Archive design allows for a maximum data rate of 64 MB/s and an average data rate of 6.4 MB/s, which produces the long-term storage capacity of approximately 200 TB/year. The ALMA correlators can producing a data up to 1000 MB/s.

As stated in [9], the purpose of the ALMA archive is to provide services for:

- Persistent archiving and retrieval for observational data.
- Observaction descriptors.
- Datacubes produced by pipeline.
- Technical and environmental data.

The main objective of the conceptual design of the ALMA Archive is to guarantee that three ALMA Regional Centres (North America, Japan and Europe) hold an identical copy of the archive at the Joint ALMA Observatory in Santiago.

ALMA front-end archive is optimized for storage and preservation, not for data query and retrieval. ASA database is inspired from ObsCore, RADAMS and Hubble Legacy Archive plus Virtual Observatory Software:

- openCADC (3.3), which is used for database access and VO access protocol
- VOView, for Web components

2.2 Square Kilometer Array

The Square Kilometer Array (SKA) is a global science and engineering project led by the SKA Organization, a not-for-profit company with its headquarters at Jodrell Bank Observatory, near Manchester. When construction starts in 2016 (according to official schedule) in Australia and in Southern Africa, thousands of linked radio wave receptors will be located to combine the signals from the antennas in each region creating a telescope with a collecting area equivalent to a dish with an area of about one square kilometer to discover how the first stars and galaxies formed after the Big Bang, how galaxies have evolved and the nature of gravity. It comprises:

- An array of dish receptors in eight African countries.
- An array of mid frequency aperture arrays in the Karoo.
- A smaller array of dish receptors and an array of low frequency aperture arrays in the Murchison Radio-astronomy Observatory in Australia.

Figure 2.2: Artist's impression of the SKA dishes. Credit: SKA Organisation/TD-P/DRAO/Swinburne Astronomy Productions

Some relevant figures and facts about SKA:

- The data collected by the SKA in a single day would take nearly two million years to playback on an ipod.
- The SKA central computer will have the processing power of about one hundred million PCs.
- The SKA will use enough optical fibre to wrap twice around the Earth.
- The dishes of the SKA will produce 10 times the global internet traffic.
- The SKA will generate enough raw data to fill 15 million 64 GB iPods every day.
- SKA will be able to detect an airport radar on a planet 50 light years away.

2.3 Murchinson Widefield Array

The Murchison Widefield Array is the first Square Kilometre Array precursor to enter full operations, generating a huge amount of information that needs to be stored for later retrieval by scientists. To store the data generated by the MWA three 1 TB hard drives every two hours are needed (it will store about 3 Petabytes at the Pawsey Center each year), so the isn not just a matter of storing the observations but how to distribute them from the MWA team in remote places, like MIT, Victoria University of Wellington in New Zealand and India.

According to Professor Andreas Wicenec, from The University of Western Australia node of the International Centre for Radio Astronomy Research (ICRAR), SKA has "now have more than 400 megabytes per second of MWA data streaming along the National Broadband Network from the desert 800 km away". Data travels through a 10 gigabit per second connection between the Murchison Radio-astronomy Observatory (MRO) and Geraldton. [1]

[1] http://www.skatelescope.org/news/pawsey-centre/

The data are not obviously intended to be fully available for everybody at every time: for instance, MIT researchers are interested in the early universe so filtering techniques to control what data is copied from the Pawsey Center archive to the MIT machines are used. By 2013, more than 150 TB of data had been transferred automatically to the MIT store, with a stream of up to 4 TB a day increasing that value.

2.4 Large Synoptic Survey Telescope

The Large Synoptic Survey Telescope (LSST) is a new kind of telescope whose wide field of view allows it to observe large areas of the sky at once. Taking more than 800 panoramic images each night, it can cover the sky twice each week. Data from LSST will be used to create a 3D map of the Universe with unprecedented depth and detail. This map can be used to locate the mysterious dark matter and to characterize the properties of the even more mysterious dark energy. Plans for sharing the data from LSST with the public are as ambitious as the telescope itself. Anyone with a computer will be able to fly through the Universe, zooming past objects a hundred million times fainter than can be observed with the unaided eye.

LSST observing will produce about 30 TB per night, leading to a total database over the ten years of operations of 60 PB for the raw data, and 30 PB for the catalog database, that will be processed using 100 TFlops. The data will be sent over existing optical fiber links from South America to the U.S.

Some of the institutional members are Google, Caltech, Harvard-Smithsonian Center for Astrophysics, Fermi National Accelerator Laboratory or STSI. [2]

Currently finishing the design and development stages, it is expected to start operating in 2022.

[2]For a full list of institutional members, browse to http://lsst.org/lsst/about/members

Chapter 3

The Virtual Observatory

The International Virtual Observatory Alliance (IVOA) was formed in 2002 with the aim to "facilitate the international coordination and collaboration necessary for the development and deployment of the tools, systems and organizational structures necessary to enable the international utilization of astronomical archives as an integrated and interoperating virtual observatory." [1] The IVOA now comprises programs from several countries and intergovernmental organizations like ESA and ESO.

The IVOA focuses on the development of standards and encourages their implementation for the benefit of the worldwide astronomical community. Working Groups are constituted with cross-program membership in those areas where key interoperability standards and technologies have to be defined and agreed upon. The Working Groups develop standards using a process modeled after the World Wide Web Consortium, in which Working Drafts progress to Proposed Recommendations and finally to Recommendations. Recommendations may ultimately be endorsed by the Virtual Observatory Working Group of Commission 5 (Astronomical Data) of the International Astronomical Union. The IVOA also has Interest Groups that discuss experiences using VO technologies and provide feedback to the Working Groups.

In this section we are not going to make a deep study of the Virtual Observatory techniques, technologies, protocols and interfaces, just those needed and selected to

[1] http://www.ivoa.net/

explain our proposal of including NoSQL into VO. Bearing in mind that the problem we are trying to address is data modelling, we will just make an overview of those aspects related with our work.

3.1 ObsTAP

A data model is a description of the objects represented by a computer system with their properties and relationships, a logical model detailing the decomposition of a complex dataset into simpler elements, like a collection of concepts and rules used in defining data model.

In 2011 IVOA proposed a new recommendation: Observation Data Model Core Components and its Implementation in the Table Access Protocol [2]. That document was intended to be a description of the interface which integrated the data modeling and data access aspects in a single service:

ObsCore data model + Table Access Protocol = ObsTAP

3.1.1 ObsCore Components Data Model

Its aim is to get the generic data model for the metadata necessary to describe any astronomical observation. In the IVOA recommendation, the data are described using UML.

3.1.2 Table Access Protocol

TAP defines a Web service for accessing tables containing astronomical catalogues. TAP is the protocol which underlies in the process of posing a query against a data source (or several data sources). The result of a query is a table, usually a VOTable. [3]

Queries which use TAP protocol can be made through several clients, like:

[2] http://www.ivoa.net/documents/ObsCore/20110502/PR-ObsCore-v1.0-20110502.pdf
[3] Support for VOTable output is mandatory, while other formats may be available.

- TOPCAT
- TAPHandle which operates fully within the Web browser
- The TAP shell, a command line interface to querying TAP servers, complete with metadata management and command line completion.
- The GAVO VOTable library, which allows embedding TAP queries in Python.

The types of queries implemented by TAP are:

- Data queries
- Metadata queries
- Virtual Observatory Support Interface (VOSI)

TAP includes support for multiple query languages, including queries specified using the Astronomical Data Query Language (ADQL [1]) and the Parameterised Query Language (PQL, under development). Other query languages are also supported, and this mechanism allows developments outside the IVOA to be used without modifying the TAP specification. Finally, it also includes support for both synchronous and asynchronous queries. Special support is provided for spatially indexed queries using the spatial extensions in ADQL.

ADQL sample query:

```
SELECT
 u.raj2000+d_alpha+d_pmalpha/cos(radians(u.dej2000))*(u.epoch-2000) AS
    ra_icrs,
 u.dej2000+d_delta+d_pmdelta*(u.epoch-2000) AS de_cicrs,
 u.pmra+d_pmalpha AS pmra_icrs,
 u.pmde+d_pmdelta AS pmde_icrs,
 u.*
FROM
  TAP_UPLOAD.T1 AS u
  JOIN ucac3.icrscorr AS c
  ON (c.alpha=FLOOR(u.raj2000)+0.5 and c.delta=FLOOR(u.dej2000)+0.5)
```

3.2 Flexible Image Transport System

Flexible Image Transport System (FITS) is an open standard defining a digital file format useful for storage, transmission and processing of scientific and other images. FITS is the most commonly used digital file format in astronomy. Unlike many image formats, FITS is designed specifically for scientific data and hence includes many provisions for describing photometric and spatial calibration information, together with image origin metadata. The FITS format was first standardized in 1981; it has evolved gradually since then, and the most recent version (3.0) was standardized in 2008.

FITS is also often used to store non-image data, such as spectra, photon lists, data cubes, or even structured data such as multi-table databases. A FITS file may contain several extensions, and each of these may contain a data object. For example, it is possible to store x-ray and infrared exposures in the same file.

FITS support is available in a variety of programming languages that are used for scientific work, including C, C++, C#, Fortran, IDL, Java, Mathematica, MatLab, Perl, PDL, or Python.

Image processing programs such as GIMP can generally read simple FITS images, but cannot usually interpret complex tables and databases.

FITS Data Format

Each FITS file consists of one or more headers containing ASCII card images that carry keyword/value pairs, interleaved between data blocks. The keyword/value pairs provide information such as size, origin, coordinates, binary data format, free-form comments, history of the data, and anything else the creator desires. In more technical terms, a FITS file is comprised of parts called Header Data Units (HDU), being the first HDU called primary HDU o primary array. This array can contain a 1-999 dimensional array. A typical primary array could contain a 1D spectrum, 2D image or 3D data cube. Any number of HDU can follow the main array, and are called FITS extensions. Currently, three different extensions can be defined:

- Image extension, a 0-9999 dimensional array of pixels, which begins with XTENSION = 'IMAGE'
- ASCII table extension which stores tabular data in ASCII formats. They begin with XTENSION = 'TABLE'
- Binary table extension stores tabular data in binary representation. Headers start with XTENSION = 'BINTABLE'

Besides, there are additional type of HDU called random groups, but only used for radio interferometry.

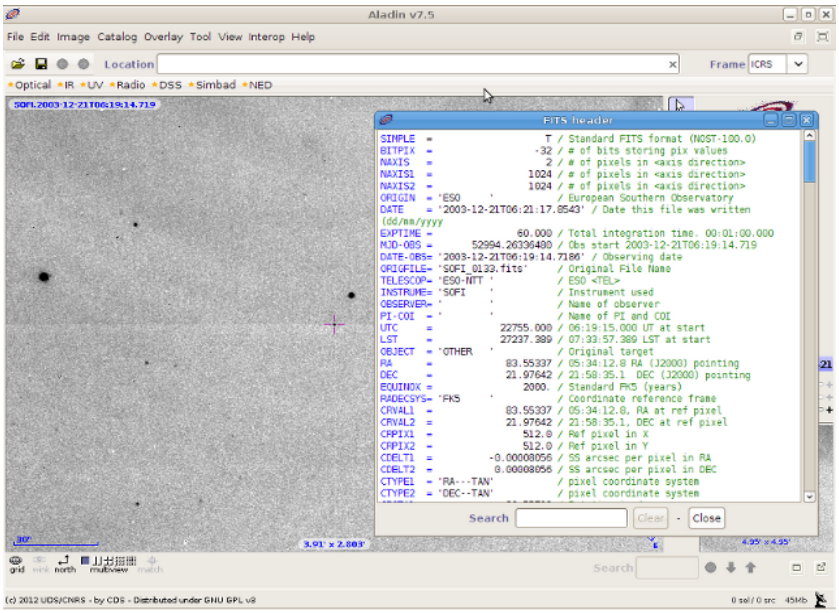


Figure 3.1: Viewing FITS header in Aladin

3.3 OpenCADC

OpenCADC (Canadian Astronomy Data Center) is a Virtual Observatory, used in ALMA Science Archive (for this reason is included in this chapter) tool which comprises several projects [4]:

[4]We do not enumerate all of them here, for a full list, go to https://code.google.com/p/opencadc/source/browse

3.3.1 Universal Worker Service

The Universal Worker Service (UWS) pattern defines how to build asynchronous (the client does not wait for each request to be fulfilled; if the client disconnects from the service then the activity is not aborted), stateful (the service remembers results of a previous activity), job-oriented (the rules for setting and arranging the parameters for a job is called Job Description Language- JDL) services.

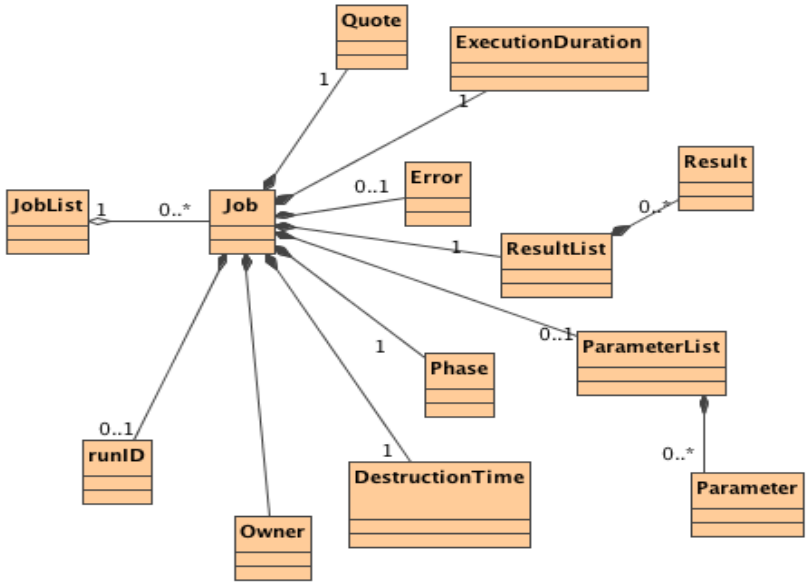


Figure 3.2: Class diagram representing UWS objects

When the execution starts, the job can adopt several states. The phases are the following:

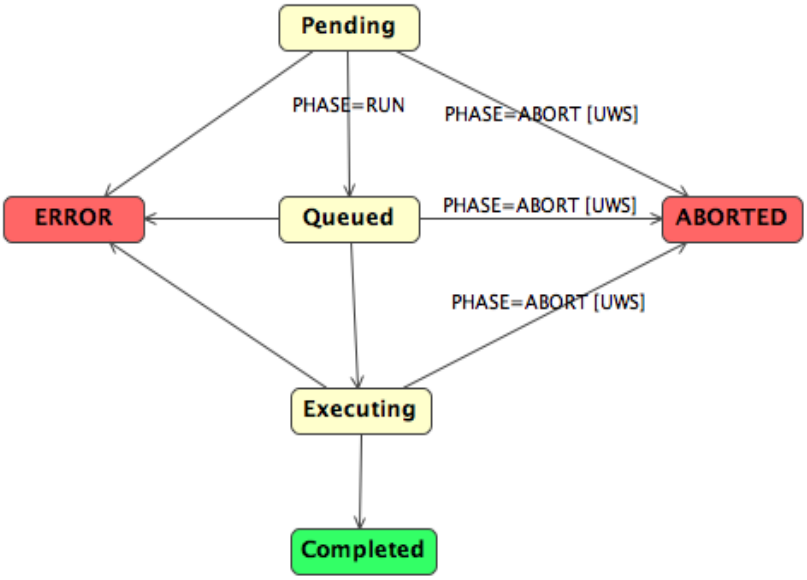


Figure 3.3: Universal Worker Server Job states

Now, we make a subtle description of the structure of the code relating UWS in OpenCADC (the cadcUWS Library), the section of the code provides Job class and plugin architecture, servlet with UWS async and sync behaviour.

JobManager

Responsible for job control.

JobPersistence

In charge of storing and retrieving Job state.

JobExecutor

It executes every job in separated threads.

JobRunner

The code that actually executes the job.

3.3.2 cadcTAP Library

The cadcTAP library is responsible of async and sync queries, where QueryRunner implements JobRunner. It also contains TAP_SCHEMA [5] DDL statements and is used by query parser to validate table and column usage.

TapQuery Interface

It has a separate implementation for each LANG (e.g. $LANG = ADQL$) specified and processess the query to local SQL.

SqlQuery

When code states $LANG = SQL$, it implements TapQuery and fully navigates it ($FROM, WHERE$ and $HAVING$ clauses).

AdqlQuery

Same as before when $LANG = ADQL$.

Plugins

- UploadManager
- TableWriter
- FileStore

QueryRunner

It implements JobRunner and sets Job state, find DataSource and uses TapSchema, UploadManager, TapQuery and TableWriter.

[5] TAP services try to be self-describing about what data they contain. They provide information on what tables they contain in special tables in TAP_SCHEMA

Chapter 4

Non-relational DBMS inside VO

Typically, modern relational databases have shown little efficiency in certain applications using intensive data, like indexing of a large number of documents, sites rendering with high traffic, and streaming sites. Typical RDBMS implementations are tuned either for small but frequent reads and writes or a large set of transactions that have few write accesses. On the other hand NoSQL DB are optimized for read and append operations, and perform outstandingly where a relational DB would slow down. They are especially fast when large amounts of data have to be queried and if we consider that speed is more important than consistency.

IVOA has a standard called Astronomical Data Query Language (ADQL) that users do not necessarily need to know, because he can pose a query with a GUI, as long as the query is translated into standard ADQL. The receiving service likewise converts the standard ADQL into whatever its own database servers need, but always inside relational model. For the reasons stated in chapter 2, we propose the use of a different approach, the NoSQL technology.

4.1 NoSQL

A non-relational database just stores data without explicit and structured mechanisms to link data from different buckets to one another.

NoSQL implementations used in the real world include 3TB Digg green markers (indicated to highlight the stories voted by others in the social network), the 6 TB of "ENSEMBLE" European Commission database used in comparing models and air quality, and the 50 TB of Facebook inbox search.

NoSQL architectures often provide limited consistency, such as events or transactional consistency restricted to only data items. Some systems, however, provide all guarantees offered by ACID systems by adding an intermediate layer. There are two systems that have been deployed and provide for storage of snapshot isolation column: Google Percolator (based on BigTable system) and Hbase transactional system developed by the University of Waterloo. These systems use similar concepts in order to achieve distributed multiple rows ACID transactions with snapshot isolation guarantees for the underlying storage system in that column, wit no extra overhead in data management, no system deployment middleware or any maintenance introduced by middleware layer.

Quite NoSQL systems employ a distributed architecture, maintaining data redundantly on multiple servers, often using distributed hash table. Thus, the system may actually escale adding more servers, and thus a server failure may be tolerated.

There are different NoSQL DBs for different projects:

- Document oriented
  - CouchDB
  - MongoDB
  - RavenDB
  - IBM Lotus Domino
- Graph oriented
  - Neo4j
  - AllegroGraph

  - InfiniteGraph
  - Sones GraphDB
  - HyperGraphDB

- Key-value oriented
  - Cassandra
  - BigTable
  - Dynamo (Amazon)
  - MongoDB
  - Project Voldemort (LinkedIn)

- Multivalue
  - OpenQM

- Object Oriented
  - Zope Object Database
  - db4o
  - GemStone S
  - Objectivity/DB

- Tabular
  - HBase
  - BigTable
  - LevelDB (BigTable open version)
  - Hypertable

They run on clusters of inexpensive machines.

4.2 Advantages and uncertainties of NoSQL

- **Elastic scaling**

  DBA have relied on scale up buying bigger servers as database load increases rather than scale out distributing the database across multiple hosts as load increases. However, as transaction rates and availability requirements increase, and as databases move into the cloud or onto virtualized environments, the economic advantages of scaling out on commodity hardware become irresistible.

  Unlike RDBMS, the NoSQL databases are designed to expand transparently to scale and they are usually designed with low-cost in mind.

- **No "need" for DBAs**

  RDBMS systems can be maintained only with the assistance of expensive and highly trained DBAs, while NoSQL databases are generally designed to require less management: automatic repair, data distribution, and simpler data models lead to lower administration and tuning requirements and costs.

- **Economics**

  NoSQL databases typically use cheap clusters servers, while RDBMS tends to rely on expensive proprietary servers and storage systems. The result is a lower cost per transaction/second for NoSQL.

- **Flexible data models**

  Even minor changes to the data model of an RDBMS have to be carefully managed and may necessitate downtime or reduced service levels. NoSQL databases have a less strict (in the worst case) data model restrictions. NoSQL allows the application to store virtually any structure it wants in a data element.

  The result is that application changes and database schema changes do not have to be managed as one unit. In theory, this will allow applications to iterate faster.

NoSQL systems have generated a lot of enthusiasm but there are still a lot of questions about its future:

- **Maturity**

  RDBMS systems have been around for a long time. NoSQL evangelists will argue that their advancing age is a sign of their obsolescence, but mature RDBMS systems are stable. Most NoSQL alternatives are in pre-production versions with many key features yet to be implemented.

- **Support**

  Most NoSQL systems are open source projects, and although there are usually one or more firms offering support for each NoSQL database, these companies often are small start-ups.

- **Analytics and business intelligence**

  NoSQL databases have evolved to meet the scaling demands of modern Web 2.0 applications. Consequently, most of their feature set is oriented toward the demands of these applications. However, data in an application has value to the business that goes beyond the insert-read-update-delete cycle of a typical Web application. Businesses mine information in corporate databases to improve their efficiency and competitiveness, and business intelligence (BI) is a key IT issue for all medium to large companies.

  NoSQL databases offer few facilities for ad-hoc query and analysis. Even a simple query requires significant programming expertise, and commonly used BI tools do not provide connectivity to NoSQL.

- **Expertise**

  There are literally millions of developers throughout the world, and in every business segment, who are familiar with RDBMS concepts and programming. In contrast, almost every NoSQL developer is in a learning mode. This situation will address naturally over time, but for now, it is by far easier to find experienced RDBMS programmers or administrators than NoSQL experts.

4.3 MongoDB: a document oriented database

MongoDB (from "humongous") is an open source document-oriented database system developed and supported by 10gen. It is part of the NoSQL family of database systems. Instead of storing data in tables as is done in a "classical" relational database, MongoDB stores structured data as JSON-like documents with dynamic schemas (MongoDB calls the format BSON), making the integration of data in certain types of applications easier and faster.

As an example, we show some JSON code inserting a document in a Mongo DB:

```
db.columns.insert( {
              table_name: "TAP_SCHEMA.schemas",
              column_name: "schema_name",
              utype: null,
              ucd: null,
              unit: null,
              description: "schema name for reference to
                 TAP_SCHEMA.schemas",
              datatype: "VARCHAR",
              size: 64,
              principal: 1,
              indexed: 0,
              std: 0
       }
);
```

10gen began Development of MongoDB in October 2007 and was not created to be just another database that tries to do everything for everyone. Instead, MongoDB was created to work with documents rather than rows, was extremely fast, massively scalable, and easy to use. In order to accomplish this, some features were excluded, namely support for transactions.

A document database is more like a collection of documents. Each entry is a document, and each one can have its own structure. If you want to add a field to an

entry, you can do so without affecting any other entry.

4.3.1 Why MongoDB?

A more detailed list of features is listed in 4.3.2 , but as a summary, we have decided to use MongoDB for these reasons:

- It is open source code (available at `https://github.com/mongodb/mongo`).
- Widely used in the NoSQL community.
- It has full index support
- Very easy to install and to connect through drivers with several programming languages like Java, Python, Ruby, C/C++, PHP or Scala.
- It supports MapReduce paradigm.

4.3.2 Main features

- **Ad hoc queries** MongoDB supports search by field, range queries, regular expression searches. Queries can return specific fields of documents and also include user-defined JavaScript functions.
- **Indexing** Any field in a MongoDB document can be indexed (indices in MongoDB are conceptually similar to those in RDBMS).
- **Replication** MongoDB supports master-slave replication. A master can perform reads and writes. A slave copies data from the master and can only be used for reads or backup (not writes). The slaves have the ability to select a new master if the current one goes down.
- **Load balancing** MongoDB scales horizontally using sharding (a shard is a master with one or more slaves). The developer chooses a shard key, which determines how the data in a collection will be distributed. The data is split into ranges (based on the shard key) and distributed across multiple shards. MongoDB can run over multiple servers, balancing the load and/or duplicating

data to keep the system up and running in case of hardware failure. Automatic configuration is easy to deploy and new machines can be added to a running database.

- **File storage** MongoDB could be used as a file system, taking advantage of load balancing and data replication features over multiple machines for storing files. This feature, GridFS, is included with MongoDB drivers and available for development languages. GridFS is used, for instance, in plugins for NGINX and lighttpd. In a multi-machine MongoDB system, files can be distributed and copied multiple times between machines transparently, thus effectively creating a load balanced and fault tolerant system.

- **Aggregation** MapReduce can be used for batch processing of data and aggregation operations. The aggregation framework enables users to obtain the same results as the SQL GROUP BY clause.

- **Server-side JavaScript execution** JavaScript can be used in queries. Aggregation functions are sent directly to the database.

- **Capped collections** Capped collections are Fixed-size collections called. This type of collection maintains insertion order and, once the specified size has been reached, behaves like a circular queue.

  Once we have seen the main features of MongoDB, we can move on to the language itself.

4.3.3 The basics

We must know four concepts to dig into MongoDB's world:

- Database: this concept is much like the RDBM counterpart.

- Collection: we can see a collection and a table as the same thing.

- Document: its equivalent in RDBM is the row, and a document is made up of fields.

- Field: is a lot like a column.

Relational	Document oriented
Table	Collection
Row	Document
Column	Field

Table 4.1: Differences between relational and NoSQL terms

SQL/Mongo syntax differences

```
-- CREATE and INSERT
CREATE TABLE tap_schema.schemas (
       schema_name  varchar(64),
       utype        varchar(512) NULL,
       description  varchar(512) NULL,
       primary key (schema_name)
);

INSERT INTO tap_schema.schemas (schema_name,description,utype) VALUES
( 'TAP_SCHEMA', 'a special schema to describe a TAP tableset', null );

db.schemas.insert( {
       schema_name: "TAP_SCHEMA",
       utype: null,
       description: "a special schema to describe a TAP tableset"}
);

-- SELECT
SELECT *
  FROM tap_schema.schemas t
 WHERE schemas.schema_name = 'TAP_SCHEMA';

db.tables.find({schema_name: "TAP_SCHEMA"});

-- DELETE
```

```
DELETE FROM TAP_SCHEMA.SCHEMAS WHERE schemas.schema_name = 'TAP_SCHEMA';

db.tables.remove({schema_name: "TAP_SCHEMA"});

-- UPDATE

UPDATE TAP_SCHEMA.SCHEMAS
   SET schemas.description = 'desc'
 WHERE schemas.schema_name = 'TAP_SCHEMA';

db.tables.update(
        {schema_name = 'TAP_SCHEMA'},
        {$set: {description = "desc"}},
        {multi:true}
);
```

4.4 FITS alternative in MongoDB

The first issue when working with FITS files is its inadequacy for storing information. In XXI century is difficult to maintain such storage model. So the first and more obvious solution would be replacing FITS headers with their counterparts in a non relational database.

Another issue when working with FITS format is the great amount of possible key-value pairs in FITS headers. A possible solution for this problem could be use the features of MongoDB to translate FITS keywords into collections. So, we could create as much documents as needed, and storing them into MongoDB. Should we need to create supertypes of FITS headers, relations are also available in MongoDB through document linking (with no physical restriction in the sense of relational constraint). In this situation the schema flexibility means that we can model documents that share a similar structure but not enforced to have to same.

Another related problem is having multiple FITS formats [1], representing the users need for storing and handling the different information requirements:

- FITS Interferometry Data Interchange (FITS-IDI) Convention: conventions adopted for registering information from interferometric telescopes recordings. Used by the VLBA.
- Single Dish FITS (SDFITS) Convention for Radio Astronomy Data: conventions used for the interchange of single dish data in radio astronomy.
- Multi-Beam FITS Raw Data Format Convention: conventions used at the IRAM 30m and APEX 12m mm/submm telescopes.
- OIFITS: A Data Standard for Optical Interferometry Data: conventions used for exchanging calibrated, time-averaged data from astronomical optical interferometers.

We show now a logical layout using MongoDB features to solve the previously posed problem. Let's suppose we have several FITS files and we have to handle them as easy as possible.

For the sake of simplicity and clarity, we have not included all FITS keywords, focusing on the abstraction.

We can profit from MongoDB store units (collections, documents and fields). We could define as much kinds of documents as needed, sort of meta-documents, considering that there is no compulsory for them having the same structure.

Solution Using just one collection and n documents, one for each kind. If we are going to work with FITS-IDI, SDFITS, MBFITS and OIFITS, the code should be like this:

```
db.fits_super.insert(
  convention: "FITS-IDI"
```

[1] The IAU FITS Working Group (IAU-FWG) is the international control authority for the FITS (Flexible Image Transport System) data format: http://fits.gsfc.nasa.gov/iaufwg/iaufwg.html

```
);

db.fits_super.insert(
  convention: "SDFITS"
);

db.fits_super.insert(
  convention: "MBFITS"
);

db.fits_super.insert(
  convention: "OIFITS"
);
```

Now, inserting the primary HDU for a FITS-IDI header in MondoDB could not be easier. We start from a very simple FITS header like:

```
SIMPLE = T  / Standard FITS format
BITPIX = 8  /
NAXIS = 0  /
EXTEND = T  /
BLOCKED = T  /
OBJECT = BINARYTB  /
TELESCOP= VLBA   /
CORELAT = VLBA   / added to header dump by EWG
FXCORVER= 4.22   /
OBSERVER= BL146   /
ORIGIN = VLBA Correlator  /
DATE-OBS= 2007-08-23  /
DATE-MAP= 2007-08-31  / Correlation date
GROUPS = T  /
GCOUNT = 0  /
PCOUNT = 0  /
```

```
END
```

This code is very easy to translate into MongoDB syntax:

```
db.my_idi_collection.insert(
    supertype: "FITS-IDI", // it simulates a foreign key!
    SIMPLE = "T",
    BITPIX = 8,
    NAXIS = 0,
    EXTEND = "T",
    BLOCKED = "T",
    OBJECT = "BINARYTB",
    TELESCOP= "VLBA ",
    CORELAT = "VLBA ",
    FXCORVER= "4.22 ",
    OBSERVER= "BL146 ",
    ORIGIN = "VLBA Correlator",
    DATE-OBS= "2007-08-23",
    DATE-MAP= "2007-08-31",
    GROUPS = "T",
    GCOUNT = 0,
    PCOUNT = 0,
);
```

Now, we have our FITS header into a database with a document structure. We keep the same approach but in a very more usable and efficient way.

4.5 MapReduce in MongoDB

MapReduce, developed by Google, is a programming model and its implementation for processing (*e.g.* raw data from telescopes) and producing (*e. g.* representations of graph structure of systems) huge amounts of data. As the runtime controls the partitioning of the input data, controlling the program execution across several hun-

dred or thousands of nodes and even controlling machine failures, the developers with low or none expertise at all in parallel programming can take advantage of this model with a very low learning curve.

MapReduce, usually, is used to solve problems involving big size datasets, up to several petabytes. For this reason, this model is used in distributed file systems, like HDFS [2].

The MapReduce model allows to write a map function which takes a key/value pair, operates on it (performs object detection) and returns a new set of key/value pairs (source list). The reduce function then aggregates/merges all the intermediate data (builds an object catalog on a stacked source list). Many problems in astronomy naturally fall into this model because of the inherent parallelizability of many astronomical tasks.

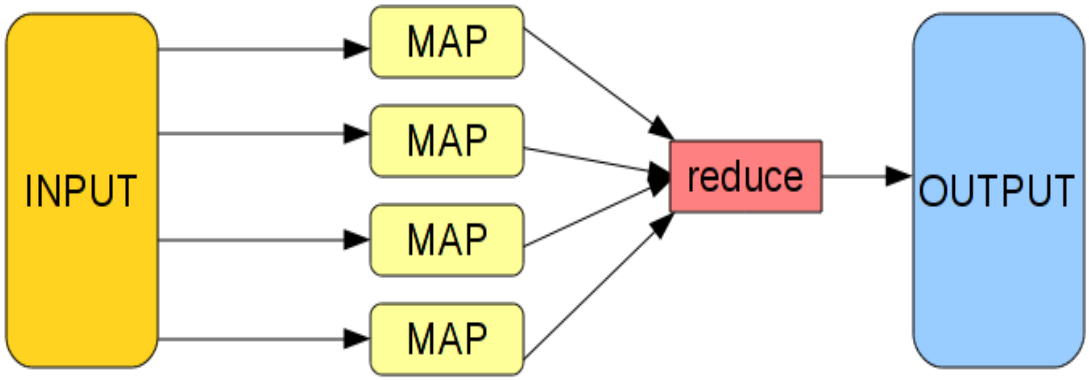


Figure 4.1: MapReduce concept

[2]For a full specification of this filesystem, go to http://hadoop.apache.org/docs/stable/hdfs_design.html

To finish this chapter, we have developed a simple MapReduce job to show its use inside the context we are working on.

```
// First, we define the map function

map = function Map() {
        var day = new Date(this.datetime.getFullYear(),
                                        this.datetime.getMonth(),
                                        this.datetime.getDate(),
                                        this.datetime.getHours());

        emit({day: day, servername: this.servername},
                {count:1, timetaken: this.timetaken});
}

// Second, we define the reduce function

reduce = function Reduce(key, arr_values) {
        var result = {count: 0, countmore5: 0, countmore10: 0};

        for(var i in arr_values) {
                if(arr_values[i].timetaken > 5000) {
                        result.countmore5 += arr_values[i].count;
                } else if(arr_values[i].timetaken > 10000) {
                        result.countmore10 += arr_values[i].count;
                }
        }
        return result;
}

// Finally, we send these two functions to the server with the desided
//  filter, specifying where do we want the data to be sent

WebLog.collection.map_reduce(map, reduce,
        {
```

```
                :query => {
                        :datetime => {'$gte' => datefilterfrom},
                        :datetime => {'$lte' => datefilterto}
                },

                :out => { reduce: "requestbyday"}
        }
)
```

4.6 Rewriting ALMA Science Archive

Chapter 5

Conclusions and future work

5.1 Conclusions

- Data generated by huge scientific projects are becoming a problem.
- Relational approach are not always suitable for any problem. Non-relational systems are not cure-all, but it has been shown they can face some problems in a more efficient way (*e.g.* MapReduce) and, in some situations, NoSQL can be a complement for existing RDBMS.
- Any new proposal should be inside Virtual Observatory frame.
- NoSQL database systems, specially -not exclusively- those document-oriented can reduce system analysis and design and can also succeed in boosting the performance of data management.

5.2 Future work

- Focusing in a workgroup inside Virtual Observatory instead of treating several aspects.
- The use of formal metrics (CoCoMo, Function Point Analysis, etc.) to plan the software design and development and the costs involved.

- Benchmarks support in order to obtain accurate data in performance improvements.
- Deciding which language to use to connect the selected DBMS.

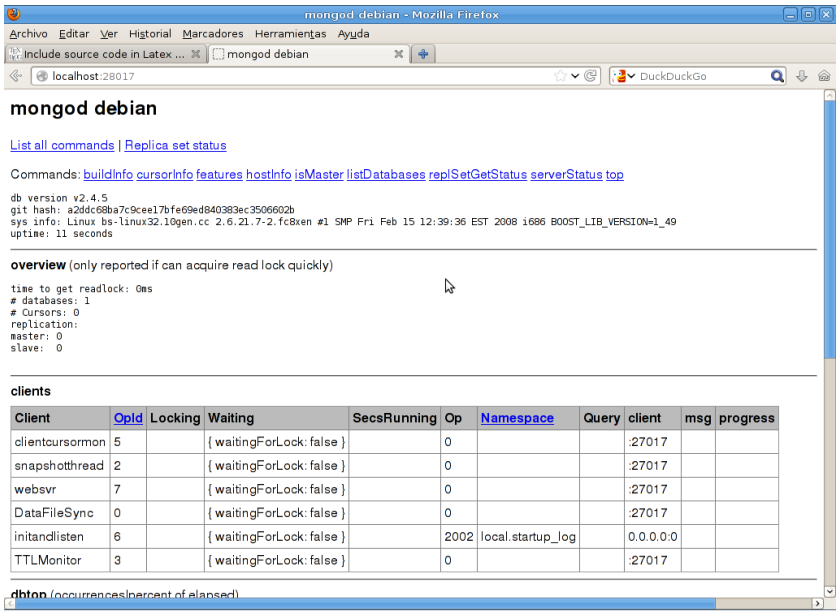
Appendix A

Getting and installing MongoDB

Go to http://www.mongodb.org/downloads and select our OS version. Download it and decompress. Supposing we are in a Linux box and that we are using the latest release (in June 2013) execute the following command:

```
./mongod --rest --dbpath /opt/mongodb-linux-i686-2.4.5/bin/data/db/
```

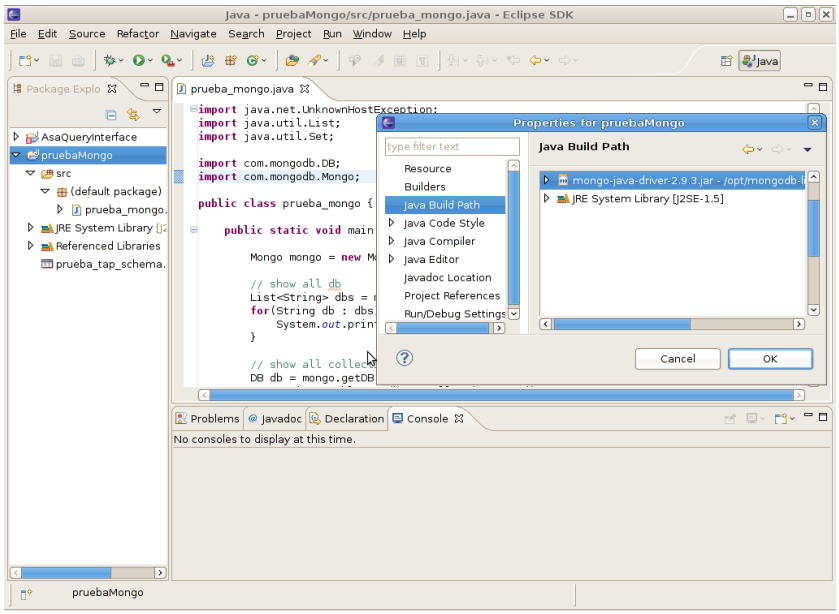
The server is now listening and waiting for connections, by default, in port 27017. As we have used the *–rest* modifier, we can point our browser to http://localhost:28017 for http diagnostic access.



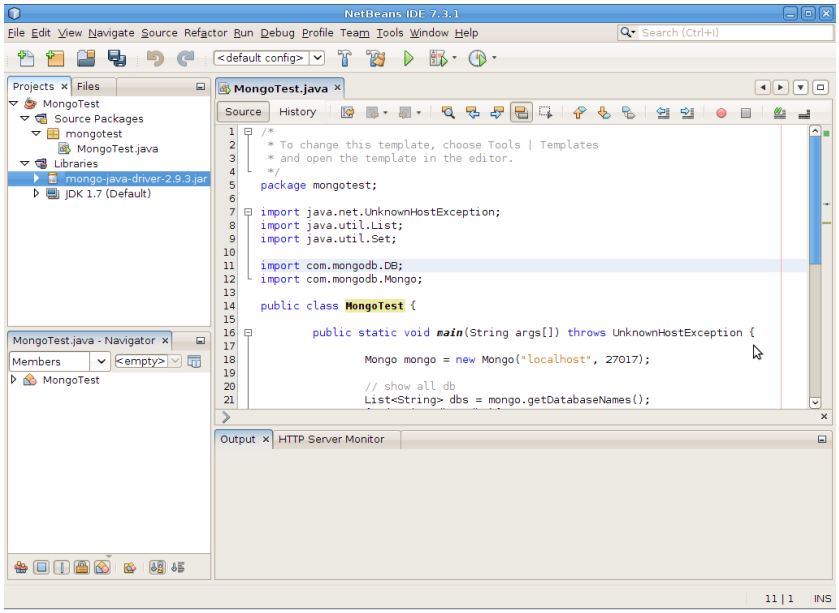
Appendix B

Configuring Eclipse and NetBeans for Java/Mongo development

- Go to http://central.maven.org/maven2/org/mongodb/mongo-java-driver/ and choose the right version.
- In Eclipse, just start a new project **File - New - Java Project**
- Right-click in **Properties** and then **Java Build Path - Libraries - Add External JARs**



- Import MongoDB methods, classed and interfaces as needed.
- In NetBeans, start a new project **File - New Project - Java Application**
- Right-click in **Libraries** and then **Add JAR/Folder**



- Import MongoDB methods, classed and interfaces as needed.

Bibliography

[1] Inc 10gen. The mongodb 2.4 manual. http://docs.mongodb.org/manual/, 2011-2013. [Online; accessed 01-December-2012].

[2] Kristina Chodorow. *MongoDB: The Definitive Guide*. O'Reilly, 2010.

[3] Kristina Chodorow. *50 Tips and Tricks for MongoDB Developers*. O'Reilly, 2011.

[4] Juan de Dios Santander Vela. Bases de datos multimedia para radioastronomía: Radams y dss-63. http://www.iaa.es/~jdsant/DEA-BBDDMultimediaParaRadioastronomia-RADAMS%2CDSS63.pdf, 2006. [Online; accessed 01-May-2013].

[5] Juan de Dios Santander Vela et al. The alma science archive: Design. ftp://ftp.eso.org/projects/adass/posters/P147.pdf, 2011. [Online; accessed 27-April-2013].

[6] Juan de Dios Santander Vela et al. The alma science archive: Implementation. ftp://ftp.eso.org/projects/adass/posters/P133.pdf, 2011. [Online; accessed 07-February-2013].

[7] Abraham Silberschatz et al. *Database System Concepts Sixth Edition*. McGraw-Hill, 2010.

[8] Tony Hey et al. editors. The fourth paradigm. data-intensive scientific discovery. http://research.microsoft.com/en-us/collaboration/fourthparadigm, 2009. [Online; accessed 31-March-2013].

[9] Sandra Etoka. A first look at the alma science archive. http://www.eso.org/sci/facilities/alma/meetings/gar-sep07/pdf/Etoka.pdf, 2012. [Online; accessed 21-March-2013].

[10] Centre for Astrophysics and Supercomputing. Scientific computing and visualisation. http://astronomy.swin.edu.au/scivis/, 2013. [Online; accessed 30-January-2013].

[11] Centre for Astrophysics and Supercomputing. Accelerating astrophysics research with gpu supercomputing. http://www.sgi.com/pdfs/4401.pdf, 2013. [Online; accessed 30-January-2013].

[12] Survey Science Group. Putting astronomy's head in the cloud. http://ssg.astro.washington.edu/, 2013. [Online; accessed 7-July-2013].

[13] Nature Vol 455 — Issue no. 7209. Big data: science in the petabyte era. http://www.nature.com/nature/journal/v455/n7209/edsumm/e080904-01.html, 2008. [Online; accessed 14-February-2011].

[14] IBM Research. Square kilometer array: Ultimate big data challenge. http://asmarterplanet.com/blog/2013/03/the-square-kilometer-array-the-world%E2%80%99s-ultimate-big-data-challenge.html, 2013. [Online; accessed 04-July-2012].

[15] John Richer. Alma, synthesis imaging and the astro-grid. http://thames.cs.rhul.ac.uk/~fionn/astro-grid-papers/john-richer.pdf, 2001. [Online; accessed 22-November-2012].

[16] skatelescope.org. The age of astronomy big data is already here. http://www.skatelescope.org/news/pawsey-centre/, 2013. [Online; accessed 09-July-2012].