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Designing and Implementing a Data Warehouse using Dimensional Modeling

by

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B.Tech., Jawaharlal Nehru Technological University, 2008

THESIS

Submitted in Partial Fulfillment of the Requirements for the Degree of

> Master of Science Computer Engineering

The University of New Mexico

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Dedication

To my family.

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Abstract

As a part of the business intelligence activities initiated at the University of New Mexico (UNM) in the Office of Institutional Analytics, a need for a data warehouse was established. The goal of the data warehouse is to host data related to students, faculty, staff, finance data and research and make it readily available for the purposes of university analytics. In addition, this data warehouse will be used to generate required reports and help the university better analyze student success activities.

In order to build real-time reports, it is essential that the massive amounts of transactional data related to university activities be structured in a way that is optimal for querying and reporting. This transactional data is stored in relational databases in an Operational Data Store (ODS) at UNM. But for reporting purposes, this design currently requires scores of database join operations between relational database views in order to answer even simple questions. Apart from affecting performance, i.e., the time taken to run these reports, development time is also a factor, as it is very difficult to comprehend the complex data models associated with the ODS in order to generate the appropriate queries.

Dimensional modeling was employed to address this issue. Dimensional modeling was developed by two pioneers in the field, Bill Inmon and Ralph Kimball. This thesis explores both methods and implements Kimball's method of dimensional modeling leading to a dimensional data mart based on a star schema design that was implemented using a high performance commercial database. In addition, a data integration tool was used for performing extract-transform-load (ETL) operations necessary to develop jobs and design work flows and to automate the loading of data into the data mart.

HTML reports were developed from the data mart using a reporting tool and performance was evaluated relative to reports generated directly from the ODS. On average, the reports developed on top of the data mart were at least 65% faster than those generated from directly from the ODS. One of the reason for this is because the number of joins between tables were drastically reduced. Another reason is that in the ODS, reports were built against views which when queried are slower to perform as compared to reports developed against tables.

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Chapter 1

Introduction

1.1 Overview

The University of New Mexico (UNM) had nearly 30,000 students enrolled in 2011 and enrollment has steadily increased by 24% as compared to the year 2001. With a wide range of programs and courses, increase in enrollment each year and sometimes more than one instructor per course, one can imagine the complexity and volume of data that would have been accumulated over the years.

To ensure success of students, it is important to track their progress each semester, i.e., to track if a student has reached a certain achievement level or not, meeting the academic needs of students, establishing and accomplishing short-term and longterm goals. Currently, only quantitative questions like number of students served or number of students receiving a passing grade in a course and so on determine measures taken to ensure progress of students. Such reports however do not enable deeper understanding, for instance, growth of a student in a given time period, comparing growth over years and factors contributing to this.

Chapter 1. Introduction

With sufficient historical data, it is now the time to make proper use of it. It is very important to make data-based decisions. With a proper understanding of the needs of business users, decision makers and policy makers, the historical data and also the new data can be logically modeled to support decision-making or business intelligence.

There are two steps to the business intelligence process. One, is to build a data model to support the reporting requirements of users which will help them track progress and success and the second is to build a predictive data model that will help the policy and decision makers by providing a better vision for the purpose of decision making.

The University of New Mexico currently has an operational data store (ODS) which is being used to serve as the back-end to generate many reports or to cater to many applications that were developed for the academic or the executive offices. But with changing needs, the database design of ODS is not efficient enough to support analytics that need to be developed.

Finally, the difficulty associated with generating the reports necessary to answer specific questions needs to be addressed. This is very difficult to comprehend the ODS table structure given the way it is defined and many users utilize the views in ODS to build their reports; a very time consuming process. Reports built on top of ODS views take a long time to run as views are not physically populated in the database, rather they are just a logical representation of data in tables.

Consider an example as in Figure 1.1 where a report is generated for student credit hours (sch) generated by faculty filtered by college in a given academic period. This report requires a drop down on the academic period and when one of them is selected, the ODS view needs to be queried and calculations need to performed on the fly. This process of querying an un-indexed view with hundreds of columns and

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ACADEMIC_PERIOD_DESC: Spring 2011					
Run Reset Save Clear Out	put Run in a new	r window			
			Level		
			Lower	Upper	Grad
College	Rank	Instructor Name			
Anderson Schools of Management	Assistant Professor	Lats, Xie		123	123
		Mahto, Rajankumar V		207	
		McNright, Reed		267	105
		Montoya, Manuel		300	
		Morales-Camargo, Emmanuel		36	60
		Patterson, Karen		81	57
		Taylor, Scott		102	135
	Associate Professor	Berman, Shawn	1.1	222	81

Figure 1.1: Student credit hours generated by faculty.

performing calculations while generating the report consumes an undesirable amount of time.

1.2 Proposed Solution

A current need, therefore involves the need to design a database that supports reporting, analytical and decision-making capabilities for executive offices at UNM. An efficient way to solve the problem mentioned in the previous section, is to use one of the industry standard methods in order to design a data warehouse that will provide a platform for running reports and to develop analytics. Bill Inmon and Ralph Kimball are the two pioneers in the theory of building data warehouses. Kimball's method of approach to developing data warehouse was chosen over Inmon's method. The design and implementation of the data warehouse using Kimball's approach as described in [1] will be the main focus of this thesis. The data warehouse will contain





Figure 1.2: ODS versus data mart performance.

data related to students, faculty, staff, finance, research, space, academic outcomes to list a few.

It is evident from the example shown in Figure 1.2 which demonstrates the performance of the data mart against ODS. When a SQL query involving joins between two tables and group by and order by clauses, the data mart returns the results in 3 seconds where as the ODS takes around 77 seconds to return the same results.

Chapter 2

Background

2.1 Existing philosophies on data warehouses

With exponential growth in data and with increasing interest to analyze and understand it to derive some knowledge out of it, it is absolutely necessary that the historical data be stored in a manner that can be easily analyzed. It is also important to derive some important statistics and various performance metrics. But this cannot be effectively implemented using the ODS. The data needs to be reorganized into a dimensional model.

A third normal form (3NF) is an entity relationship (ER) model where the tables are normalized to a state where there is no data redundancy, attributes in an entity are solely dependent on whole of the primary key of the entity. A primary key can be just one attribute or a composite key consisting of two or more attributes.

The 3NF was initially defined by E.F.Codd and was later expressed differently by Carlo Zaniolo. According to [5], it is defined as follows.

A table is in third normal form (3NF) if and only if for every nontrivial

functional dependency $X \to A$, where X and A are either simple or composite attributes, one of two conditions must hold. Either attribute X is a superkey, or attribute A is a member of a candidate key. If attribute A is a member of a candidate key, A is called a prime attribute. Note: a trivial FD is of the form YZ $\to Z$.

A 3NF ER model is good design to handle transactional data. Examples for transactional data are courses taken by students in each term, proposals filed by each principal investigator each year and so on. This type of design is good for performing quick inserts, updates and deletes because the tables usually have a small number of fields with foreign keys to other tables. The reason behind this is that, to generate a simple report one would end up joining scores of tables in a 3NF environment which ends up being very time and resource (hardware) intensive. Apart from this, the model becomes very complex very quickly as a result of which it becomes very difficult to understand and navigate the model even for a developer let alone a business user.

To address this problem, Bill Inmon in Figure 2.1 proposed an idea with a topdown approach and named the system as corporate information factory (CIF) defined in [2]. The components of a CIF include a data warehouse which is built in 3NF and individual de-normalized data marts which are populated from the data warehouse. These data marts cater to individual business process needs. Reporting cubes are built as required on top of the data marts. The data warehouse as defined by Bill Inmon, contains enterprise data without any redundancy at the lowest level of detail i.e., transactional data in 3NF.

According to Inmon, a data warehouse is subject-oriented, non-volatile, integrated, time-variant and has no virtualization.

Another pioneer, Ralph Kimball proposed his own version of a data warehouse



Figure 2.1: Inmon data warehouse Architecture [2].

Figure 2.2 which is termed as a bottom-up approach. A data warehouse as defined by Kimball in [1] is the conglomeration of all individual data marts. These data marts are built using dimensional modeling. Each data mart contains data specific to a business process. This method was chosen as part of business intelligence architecture that has been implemented at UNM.

The benefits of dimensional modeling technique are:

Better data navigation and presentation: The logical data model is designed in a way that is easy to understand and navigate even for business users. This enables them to build their own reports.

Easy and low-cost maintenance: The data is stored in the same way as it is presented unlike in the case of relational databases where in most cases views are built in order to build any reports. This increases the maintenance cost in the case of relational databases or ODS.

Better performance: Most reports require summarized data which results



Figure 2.2: Kimball data warehouse Architecture [1].

in a slower performance due to on-the-fly calculations in the case of non-indexed views in ODS. In the case of dimensional modeling, summarized tables are built as required. It also allows the ability to store data history in a manner that is easy to query and build reports on. Such a design delivers faster query performance and to drill down and drill across hierarchies.

2.2 Differences between Inmon and Kimball methods of approach to data warehousing

Data warehousing is the process of building a data warehouse. Reports are currently being built on top of the views in ODS. The ODS is not actually optimized for reporting or analytics.

Now in the case of Inmon's approach of data warehousing, the architecture suggests that a 3NF data warehouse be built as the next step, which would contain

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all the data in the organization, and then build a data marts layer to support the reporting layer. In our case, with ODS and a staging layer in place, it is not optimal in terms of time and money to build another layer of 3NF data warehouse which can be seen as nothing but another staging layer for the data. This data warehouse has no independent deliverable of its own.

In the case of Kimball's approach however, the idea is to build the data marts layer right after the staging layer. These data marts cater to individual business processes identified. All the data marts together then form the data warehouse as defined by Kimball. The common dimensions between the business processes are however shared between them, without building a separate version of it, to maintain a single version of truth and make it simple to update. These are called conformed dimensions. Using this approach, we do not need a second staging layer and since the data marts are specific to a business process, reports can be generated out of it, without waiting for rest of data marts to be designed and implemented.

Therefore, considering reasons like cost-effectiveness and the ability to deliver reports quickly, it has been decided that the Kimball methodology would be used for designing a data warehouse to address our problem.

2.3 Definitions

A few of the common terms of data warehousing used in this thesis are explained below as defined by Kimball in [1], [4] and [6].

A **Fact table** consists of the foreign keys to all the dimension tables in the schema and facts that are numerical business measurements. It is a transaction based table.

A **Dimension table** is an explicitly defined subject area in a business. it is a non-transaction based table.

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Conformed dimensions are standardized tables modeled once and shared across multiple fact tables in the same schema or even a different data mart. This is determined by the Bus Matrix. These tables support the ability to drill across and integrate data from multiple business processes. The main advantage of using conformed dimensions is to save storage space. It is also easier to maintain and refresh one table versus multiple versions of the same table.

An enterprise data warehouse bus matrix is the architectural blueprint providing the top-down strategic perspective to ensure that data can be integrated across the enterprise.

The **grain** is defined as the lowest level of detail in a table. The grain of a fact/dimension table is the definition of what constitutes a unique fact/dimension table record.

A factless fact table is a fact table that contains no facts but captures certain many-to-many relationships between the dimension keys. Most often it is used to represent events or provide coverage information that does not appear in other fact tables. Some examples include tracking student attendance or registration events, identification numbers of building or facility.

The **business key or natural key** identifies a business entity. Examples include student_id, course_id and program_id.

The **primary key** uniquely identifies a record in a table. A primary key can consist of a single field or multiple fields and cannot be a NULL value.

The **Foreign key** is a single field or multiple fields which uniquely identifies a record in another table.

The **Surrogate Key** uniquely identifies a record in a dimension table. It is usually ETL generated and provides the means to maintain data warehouse information

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when dimensions change. One simple way improve performance of queries is to use surrogate keys. Surrogate keys can be derived from the existing natural keys or it can be a simple integer. As an example, a surrogate key can be a composite key, being the combination, student_id + academic_period or just an integer value generated by the ETL program while a record is being inserted the table. Using integer surrogate keys means a thinner fact table and the thinner the fact table, the better the performance.

The **star schema** is a dimensional design for a relational database. In a star schema, related dimensions are grouped as columns in dimension tables, and the facts are stored as columns in a fact table. The star schema gets its name from its appearance: when drawn with the fact table in the center, it looks like a star or asterisk.

The **snowflake schema** is a variation on the star schema. When principles of normalization are applied to a dimension table, the result is called a snowflake schema.

A degenerate dimension is present in the fact table. For example this may be a transaction number, invoice number, ticket number, or bill-of-lading number, that has no attributes and hence does not join to an actual dimension table. A junk dimension is present in the fact table. Examples include boolean indicator or flag fields such as enrolled_flag, ethnicity indicators, etl_timestamp and so on.

Chapter 3

Design and Implementation

Kimball's approach was chosen as the base architecture for supporting business intelligence at UNM. The conceptual model and logical model were designed based on the requirements analysis and source data analysis.

3.1 Process of building a Kimball data warehouse

Various steps involved building a Kimball data warehouse include business/user requirements gathering, requirements analysis, source data analysis, target database logical model design, target database physical design, source data cleansing, extract transform load (ETL) process design, data validation, report development and performance analysis. All design principles are based on Kimball's approach to data warehousing as defined in [1].

Different approaches were used for gathering requirements including phone interviews, personal interviews with individual end users and stake holders and also group meetings. A requirements document was prepared in agreement with the business.

Chapter 3. Design and Implementation



Figure 3.1: Kimball data warehouse life cycle [1].

Requirements analysis was done keeping the structure of the source data in mind. A conceptual data model was prepared which laid out a high level structure of the entities and the relationships between them after identifying separate business needs. Facts and dimensions were identified. Grain of the tables was determined. Conformed dimensions are identified using the business matrix. A data mart may have multiple star schemas but dimensions can be shared between different fact tables or business processes. For example, the student data mart has multiple star schemas. One star schema is dedicated to the academic progress of the student, student detail, program, department, courses, instructors and person data. The second schema captures financial aid. Another star schema is dedicated to applications and admissions.

Next, the logical data model and the physical data model (for Oracle 11g environment) were designed using licensed software, Toad data modeler. There were some

design issues which needed special handling including many-to-many relationships and slowly changing dimensions which are explained later in this thesis.

A document was prepared which contained the source table fields mapped to the target table fields. This is called the source-to-target mapping document. Preparing this mapping document is very essential as it is the base for the extract transform and load (ETL) development process.

The next step in the data warehousing process is the ETL design. $SAS^{\mathbb{R}}$ data integration software was used to perform the ETL tasks.

Using the data mart as the back end, HTML reports as required by various business units were designed using Web Focus which is the primary reporting tool currently being used at UNM.

3.2 Business Matrix

The business matrix Figure 3.2 is tabular representation of the business process versus the dimension tables. This is an agile modeling method and is done so as to identify the Conformed dimensions. In the figure, we can see that the dimensions academic calendar, course, department and person are shared between multiple business processes. These are called conformed dimensions.

3.3 Grain

The grain of a table is defined as its lowest level of detail. The tables in Figure 3.3 and Figure 3.4 show the grain of the fact and dimension tables in the student data mart. For example, the student enrollment fact table has one row per student per

		IDENTIFIED DIMENSIONS						
BUSINESS PROCESSES	400,000 and 100 and 10	Course	Department	Student	Post and	Instructor	Financial Aid	Person
Student Enrollment	X	Х		Х				Х
Course Enrollment	X	Х						
Department Enrollment	X		Х					
Program Enrollment	X				Х			
Instructional Assignment	X	Х	Х			Х		Х
Financial Aid	X						Х	

Figure 3.2: Business Matrix.

FACT TABLES	ATOMIC GRANULARITY	FACTS
Student_Enrollment_Fact	1 row per student, per course, per term	Enrollment,Grade
Course_Enrollment_Fact	1 row per course, per term	Enrollment, Grade
Department_Enrollment_Fact	1 row per department, per term	Enrollment,Grade
Program_Enrollment_Fact	1 row per program, per term	Enrollment,Grade
Instructional_Assignment_Fact	1 row per instructor, per course, per term	Primary Indicator, % Responsibility
Financial_Aid_Fact	1 row per student, per term	Amount Awarded

Figure 3.3: Granularity of fact tables.

course per semester which means that this table will have all the records of a student with respect to all the courses the student was ever enrolled in. Also mentioned are the primary facts in that table. Similarly the dimension tables granularity in Figure 3.4 shows a few main fields in that table.

3.4 Logical and physical design

After designing the business matrix and determining the granularity of tables, the next step is logical designing of the data mart. This was done using the Toad data

DIMENSIONS	ATOMIC GRANULARITY	DATA FIELDS
Academic_Calendar_Dim	1 row per academic period	Academic Year and Aid Year Hierarchies
Course_Dim	1 row per course, per academic period	Acad. Period, Course No., Sections, CRN
Department_Dim	1 row per department	Department Hierarchy Information
Student_Dim	1 row per student, per academic period	Student program, campus, college, dept.
Program_Dim	1 row per program	Program Information
Person_Dim	1 row per person	Demographic Information
Financial_Aid_Dim	1 row per fund_code	Fund Information
Instructor_Dim	1 row per instructor	Instructor Department, Rank
Instructor_Group_Dim	1 row per instructor group	Instructor Group Key
Instructor_Group_Bridge	1 row per instructor, per instructor group	Instructor Group Key, Instructor Key

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Figure 3.4: Granularity of dimension tables.

modeling tool and most of the business processes or subject areas mentioned in the business matrix diagram were designed using the star schema approach. In a star schema, there is a fact table, which has all the foreign keys to the dimension tables in that subject area and the facts. The dimension tables have data related to different areas like person, course, student, department, program and so on. Figure 3.5 shows the student subject areas within the enterprise university data warehouse. Other subject areas include finance, research and so on. In the student data mart, there are different aspects that have been identified like student enrollment, course enrollment, admissions, financial aid and some summary tables. Each of these aspects have their dimension tables and a fact table. For example, the student enrollment schema has a fact table named student_enrollment_fact and dimension tables academic_calendar_dim, student_dim, course_dim and instructor_dim. The dimension tables have a surrogate key apart from the natural keys. This is done in order to uniquely identify each record in the table. This surrogate key is usually a number and is automatically generated when the table is being loaded. Figure 3.6 shows the student enrollment star schema with the student_enrollment_fact table having all the foreign keys to the surrounding dimension tables and then the actual facts like grades and credit hours. Similarly Figure 3.7 shows the

Chapter 3. Design and Implementation



Figure 3.5: Student data mart schema.

course_enrollement. Figure 3.8 shows the instructor course assignment fact schema. This schema captures all the courses assigned to various instructors over years. It shows a instructional_assignment_fact table having facts like percent responsibility of each instructor assigned to a course with multiple instructors. The fact table is connected to the required dimensions. It can also be observed, the table and field names are quite intuitive and are easily understood by anyone.

Indexing the tables appropriately and partitioning the tables if required are part of the physical design. After the physical design, the table definitions are captured into a data definition language (DDL) file and are installed on the database.

3.5 Solutions provided by the data mart design

The following is a non-comprehensive list of solutions offered by this Data Mart:

Student level facts and statistics: The data mart can answer questions at the most transactional level about students like courses registered by a student in a given term, final grades of each student in a course, enrolled date and drop date of a course and bio-demographic information.

Course level facts and statistics: These include total active enrollment in a term in a course, total drop outs out of a course, instructor details of a course including cases multiple instructors per course, total enrollment in each course and enrollment categorized by ethnic groups, average grade of all students in each course and average grade by ethnicity.

Instructor level facts and statistics: These statistics include all courses taught by an instructor in a given term, percentage contribution of each instructor in a course with multiple instructors, bio-demographic information about instructors and HR and departmental information about instructors.

Department level facts and statistics: Examples for department level statistics that are provided by the data mart include courses offered by a department in a given term and their corresponding facts and summarized reports include enrollment in each course offered by a department over many semesters and grade distribution, i.e., number of students in each grade, in each course offered by a department in a semester.

Program level facts and statistics: The data mart provides program level statistics like courses in a program in a given term and their corresponding facts. Some of the summarized level of information includes count of students registered in a program over a period of many semesters.

Financial aid facts and statistics: These are statistics on students who have been awarded financial aid in a given term. The data mart can also be used to see how many students received a Pell grant or submitted the free application for Federal

Student Aid (FAFSA) in a semester. This data can be analyzed together with the grades data resulting in interesting information.

Applications and admissions statistics: These include account of those who have submitted their test scores and prior GPAs to UNM, count of applicants to each program in each academic period versus count of admitted students, average test scores of applicants who were admitted into each department or program, distribution of admitted students with various test scores and so on.

3.6 Further optimization of the data mart for reports

Sometimes, it is required to see reports that need aggregation of the fact tables. Examples include reports needed by some of the executive offices at UNM which require summarized data from the student_enrollment_fact table rolled up to the department, program, degrees awarded or student data summarized by term and level. To generate the appropriate reports according to these requirements, the reporting tool needs to perform aggregation on the fly. This may take a lot of time depending on the complexity.

3.6.1 Building summary fact tables

To overcome this issue, summary fact tables have been designed to readily address such report requirements. Figure 3.9 shows a few summary fact tables that have been designed as a part of the student data mart. The summary fact tables contain rolled up version of the actual transaction level data. For instance, the program_enrollment_fact table has one record per program per semester which states

facts like total enrollment in the program and enrollment distribution by ethnicity. Similarly, the grain of student_level_summary_fact table is one record per student and contains cumulative data of the student until that point of time since inception. The table student_term_summary_fact has one record per student per semester and keeps track of student GPA, credit hours and such for each semester. The degreesawarded_fact table has degrees awarded to all the students at UNM. These tables enable quicker reporting as on-the-fly calculations can be avoided. In spite of it being true that more storage is required, the creation of these summary tables can be justified considering the facts that storage is not very expensive and the tremendous performance benefit the creation of these tables has to offer.

3.7 Design issues

3.7.1 Resolving many-to-many relationships

It is impossible to implement many-to-many relationships between tables, on a physical database except by having another table between them which splits the manyto-many relationship to many-to-one and one-to-many relationships. In Kimball's dimensional modeling, this is called the bridge table [1].

In this design, the student_enrollment_fact table takes care of the many-to-many relationship between student-dimension and course-dimension tables. However, at UNM, we also have multiple instructors for some courses. To implement this, an instructor_group dimension table was introduced which has an instructor_group_key attribute. There is a one-to-many relationship between instructor_group dimension table and student_enrollment_fact table.

An instructor_group_bridge table is introduced which has an instructor_group_key and instructor_key (from the instructor_dimension) having many-to-one relationship to both instructor_group dimension and instructor_dim tables. Thus we are breaking up a many-to-many relationship into two many-to-one relationships.

3.7.2 Implementing slowly changing dimensions (SCD)

The fact tables see frequent insertion of new records in sync with the transactions taking place. Thus, fact table grows quickly over time, but updates to these records are rare. In the case of Dimension tables, the data growth is relatively slow, however updates may be necessary to those records with changes to the business rules, or student data, personal data and so on.

These changes may or may not be tracked based on business requirements. The following are some of the different ways to do so. These methods are based on Kimball's approach to slowly changing dimensions in a data warehouse in [1].

SCD TYPE 1: Overwrite existing record

In slowly changing dimension Type 1 [1], the existing attribute is updated, i.e., it is over-written with the new value. This type of SCD is used when the business requirements state that no history of data is required for any analysis.

In the example Figure 3.11 shown below, the address is replaced with the new value.

SCD TYPE 2: Add a New Record

In this type of slowly changing dimension, a new record is added whenever there is a change, instead of updating the existing record with the new value. This is done with the help of two date fields, effective_start_date and effective_end_date. These

dates are manipulated, whenever there is a change [1].

This type of SCD, is the most commonly used and preferred because of its ability to store unlimited history as well as to store the time of that change.

In the example Figure 3.12, The effective_end_date field is initially populated with a random future date value, preferably a few years away, keeping the life cycle of the data warehouse in mind. Now, whenever there is a change to address, the effective_end_date is changed to the when the address effectively ends, and a new record is added with the new address value along with the respective effective_start_date. Also, there is another field called current_flag which is a boolean value indicating whether the record is active or not. This column in included in order to further optimize the query performance on this table when finding active or inactive records.

For example, to pull the active/current records, one may just look for current_flag = 1 instead of looking at (or joining on) the effective_start_date and effective_end_date values.

SCD TYPE 3: Add new column

In slowly changing dimension type 3, a new field is introduced to keep limited track of the changes [1].

This type of SCD is used when the business requirements state that only limited history needs to be stored in the data mart. If there is a pre-determined value for the number of versions of history being tracked, this type of SCD handling is helpful in reducing redundancy and thus save storage space.

In the example Figure 3.13, assuming that we are keeping history of two values for social security number, one field is the current social security number called SSN and the previous or expired value is under the field name Prior SSN. Whenever a
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change is reported, the prior SSN field is updated with the existing value in SSN field and the SSN field is updated with the new value. We could also have dates to keep track of when the change has occurred.

Hybrid SCD (SCD Type 6): SCD Type 1 + Type 2

There are many types of hybrid slowly changing dimensions, one of which is a combination of SCD types 1 and 2. This is also termed as SCD type 6 [1].

In this type of SCD, as in Figure 3.14, one field in the table can be a Type 2 SCD (field: Address) and another is handled as a type 1 SCD (field: SSN). Initially we have a record with an address and SSN. When there is a change in the address, it is updated according the rules of SCD type 2 i.e., updating the effective_start_date, effective_end_date and current_flag fields. However when there is a change in the SSN, it is updated according to the SCD type 1 rules which is to just replace or over-write the old value.



Figure 3.6: Student Enrollment Star Schema.





Figure 3.7: Course Enrollment Star Schema.





Figure 3.8: Instructor Course Assignment Fact Schema.

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Program_Enrollment_Fact	
Time_key	Number
Progra m	Varchar2(
Term	Varchar2(
Total_Enrollment	Number
His pan ic_En rollme nt	Number
African_American_Enrollment	Number
American_Indian_Enrollment	Number
White_En rollment	Number
ETL_Timestamp	Times tam

DegreesAwarded_Fact					
Time_key	Number				
Biodemo_key	Number				
Student_key	Number				
Degree_Awarded	Varchar2(30)				
Final_GPA	Number(7,3)				
Grad_Status	Varchar2(4)				
Campus_Code	Varchar2(3)				
Colleg e_Code	Varchar2(2)				
Department_Code	Varchar2(4)				
Program	Varchar2(12)				
Ad viso r_ld	Varchar2(9)				
ETL_Time stamp	Timestamp(6)				

STUDENT LEVEL SUMMARY	' FACT
PERSON KEY	Number
STUDENT ID	Varchar2(9)
PERSON UID	Number
NAME	Varchar2(255)
NO_OF_COURSES_ENROLLED	Number
GPA_TYPE	Varchar2(1)
GPA_TYPE_DESC	Varchar2(11)
ACADEMIC_STUDY_VALUE	Varchar2(63)
ACADEMIC_STUDY_VALUE_DESC	Varchar2(255)
GPA	Number
GPA_CREDITS	Number
CREDITS_ATTEMPTED	Number
CREDITS_EARNED	Number
CREDITS_PASSED	Number
QUALITY_POINTS	Number
ETL TIMESTAMP	Timestamp(6)
STUDENT TERM SUMMARY	FACT
TIME KEY	Number
PERSON_KEY	Number
STUDENT_KEY	Number
TERM	Varchar2(6)
STUDENT_ID	Varchar2(9)
PERSON_UID	Number
NO_OF_COURSES_ENROLLED	Number
GPA_TYPE	Varchar2(1)
GPA_TYPE_DESC	Varchar2(11)
ACADEMIC_STUDY_VALUE	Varchar2(63)
ACADEMIC_STUDY_VALUE_DESC	Varchar2(255)
GPA	Number
GPA_CREDITS	Number
CREDITS_ATTEMPTED	Number
CREDITS_EARNED	Number
CREDITS_PASSED	Number
QUALITY_POINTS	Number
ETL TIMESTAMP	Timestamp(6)

Figure 3.9: Summary Fact Tables.



Figure 3.10: Instructor Bridge Table.

ORIGINAL RECORD					
Кеу	Person_Id	Name	Address		
1	101	xyz	1 UNM, ABQ, NM		
	NEW RECORD				
Кеу	Person_Id	Name	Address		
1	101	xyz	2 Gallup, NM		

Figure 3.11: Slowly Changing Dimension Type 1.

Chapter 3. D	esign	and	Impl	ementation
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	ORIGINAL RECORD					
Кеу	Person_Id	Name	Address	Eff.Start Date	Eff.End Date	Current_Flag
1	101	xyz	1 UNM, ABQ, NM	1/1/2010	9/9/2099	1
	NEW RECORDS					
Кеу	Person_Id	Name	Address	Eff.Start Date	Eff.End Date	Current_Flag
1	101	xyz	1 UNM, ABQ, NM	1/1/2010	1/1/2013	0
2	101	xyz	2 Gallup, NM	1/2/2013	9/9/2099	1

Figure 3.12: Slowly Changing Dimension Type 2.

Кеу	Person_Id	Name	SSN				
1	101	xyz	1000001				
	NEW RECORD						
Кеу	Person_Id	Name	SSN	Prior SSN			
1	101	xyz	123456789	1000001			

Figure 3.13: Slowly Changing Dimension Type 3.

	ORIGINAL RECORD						
Кеу	Person_Id	Name	Address	Eff.Start Date	Eff.End Date	SSN	Current_Flag
1	101	xyz	1 UNM, ABQ, NM	1/1/2010	9/9/2099	1000001	1
			NEW RECORDS	- Address chang	ge - SCD Type 2	2	
Кеу	Person_Id	Name	Address	Eff.Start Date	Eff.End Date	SSN	Current_Flag
1	101	xyz	1 UNM, ABQ, NM	1/1/2010	1/1/2013	1000001	0
2	101	xyz	2 Gallup, NM	2/1/2013	9/9/2099	1000001	1
			NEW RECORD	S - SSN change	- SCD Type 1		
Кеу	Person_Id	Name	Address	Eff.Start Date	Eff.End Date	SSN	Current_Flag
1	101	xyz	1 UNM, ABQ, NM	1/1/2010	1/1/2013	1000001	0
2	101	xyz	2 Gallup, NM	2/1/2013	9/9/2099	123456789	1

Figure 3.14: Hybrid Slowly Changing Dimension.

Chapter 4

Extract Transform Load (ETL)

4.1 Populating the data mart

Extract transform and load (ETL) process is implemented after source tables have been analyzed and target tables have been designed and installed in the database. The SAS[®] data integration (DI) studio is the ETL software piece of the SAS[®] suite of products. It has a more complex learning curve compared to some other ETL tools like Pentaho or Talend; however, f it offers more flexibility in scheduling parallel jobs and work flows.

4.2 Logical steps in ETL

The method used for the ETL process is based on the principles from [3] and the technical details of ETL implementation is based on methods defined in [7]. After the data mart has been implemented on the target database, staging tables are designed. Data from various sources including ODS, pre-award research data stored

Chapter 4. Extract Transform Load (ETL)

in a database system called cayuse, space data stored in a database system called famis is brought into a staging area using ETL jobs. Here the data is cleansed and validated along with other quality checking and improvement processes as required. From the staging tables, data is brought into the data mart tables using SAS[®] data integration studio. First, records are inserted into the dimension tables from the respective staging tables along with ETL generated surrogate keys and then fact tables are loaded by capturing numerical columns from the staging tables and the corresponding surrogate keys from the dimension tables as foreign keys.

The first step in ETL is to define libraries in DI studio that contain connection information to back end database servers. After this, metadata or definitions of tables or views from the source and target environments are imported into the DI studio environment. As a next step, the staging tables are populated using simple transformations in DI studio. Further steps include loading the dimension tables and finally loading the fact tables.

The dimension tables are loaded before the fact tables. The reason behind this is that the fact table contains foreign keys to records from the dimension tables and needs to pick it up while being loaded. This helps to maintain referential integrity of the fact table i.e., a record exists in a fact table if and only if all the corresponding key records exist in the respective dimension tables.

Source to target mapping: In the DI studio, within some transformations like 'table loader', and 'splitter', we have an option to select what input columns we need and then map it to the respective output column. This is done automatically if the source and target column names are same, otherwise the columns need to be mapped manually using point-click and drag method. Figure 4.1 shows such an example.

Populating a staging table: Figure 4.2 demonstrates use of simple transformations like 'extract' and 'insert rows' to populate a staging table called

	😡 finance_fact_2005 -> Join *											
	C Up ▶ Run = Stop ¾ (3) (3) (3) (3) (3)											
Γ	I]]] - ⊒ ⊒]₀ - 1] ,	J 🛧 🖊 📑 - 4	- 🔊 🛯 X-								
	Source	e table: All Tables		·		III	Tan	get ta	ble: Joir	(W 19W 1IV9)		
	#	Column	Column Description	Table	•		#	11		Column	Column Description	
	1	FISCAL_TIME_KEY	FISCAL_TIME_KEY	FISCAL_TIME_DI			1	-+-	4	INDEX_CODE	INDEX_CODE	
	2	A FISCAL_YEAR	FISCAL_YEAR	FISCAL_TIME_DI			2	0)0	4	ACCOUNT	ACCOUNT	
	3	A FISCAL_PERIOD	FISCAL_PERIOD	FISCAL_TIME_DI			3	-+-	(SUM_ADOPTED_BUDGET	SUM_ADOPTED_BU	
	4	A INDEX_CODE	INDEX_CODE	STG_OPERATING		HT // A	4	0)0	(SUM_BUDGET_ADJUST	SUM_BUDGET_ADJ	
	5	A FISCAL_YEAR	FISCAL_YEAR	STG_OPERATING		- \\\ /// ///	5	-+-		SUM_YEAR_TO_DATE	SUM_YEAR_TO_DA	
	6	A FISCAL_PERIOD	FISCAL_PERIOD	STG_OPERATING		- \\\ / /// A	6	•••	(SUM_ENCUMBRANCES	SUM_ENCUMBRAN	
	7	A FUND	FUND	STG_OPERATING		ь W. ////д	7	-1-	(SUM_BUDGET_RESERV	SUM_BUDGET_RES	
	8	A ORGANIZATION_CODE	ORGANIZATION_C	STG_OPERATING		$\mathbb{N}/\mathbb{N}/\mathbb{N}$	8	-+-	(SUM_ACCUMULATED	SUM_ACCUMULATE	
	9	ACCOUNT	ACCOUNT	STG_OPERATING		$X \times ////$	9	-+-	(SUM_GRANT_ACTIVITY	SUM_GRANT_ACTI	
	10	A PROGRAM	PROGRAM	STG_OPERATING		ь V/XX////л	10	•••	(SUM_REMAINING_BAL	SUM_REMAINING	
	11	ACTIVITY	ACTIVITY	STG_OPERATING		WXXXX////	11	-+-	(CURR_ADOPTED_BUD	CURR_ADOPTED_B	
	12	SUM_ADOPTED_BUDGET	SUM_ADOPTED_BU	STG_OPERATING		YXXX/////	12	-+-	(CURR_BUDGET_ADJUS	CURR_BUDGET_AD	
	13	3 SUM_BUDGET_ADJUSTME	SUM_BUDGET_ADJ	STG_OPERATING		-XXX/XX///	13	-+-	(CURR_YEAR_TO_DATE	CURR_YEAR_TO_D	
	14	3 SUM_YEAR_TO_DATE_AC	SUM_YEAR_TO_DA	STG_OPERATING		-/XXXXX//	14	-+-	(CURR_ENCUMBRANCES	CURR_ENCUMBRA	
	15	3 SUM_ENCUMBRANCES	SUM_ENCUMBRAN	STG_OPERATING		1/XXXXX/A	15	-+-	(CURR_BUDGET_RESER	CURR_BUDGET_RE	
	16	SUM_BUDGET_RESERVAT	SUM_BUDGET_RES	STG_OPERATING		\sim	16	-+-	(CURR_ACCUMULATED	CURR_ACCUMULAT	
	17	3 SUM_ACCUMULATED_BU	SUM_ACCUMULATE	STG_OPERATING		$\sim 1/1000$	17	-+-	(CURR_GRANT_ACTIVITY	CURR_GRANT_ACT	
	18	3 SUM_GRANT_ACTIVITY	SUM_GRANT_ACTI	STG_OPERATING		$\mathbf{V}///\mathbf{X}\mathbf{X}\mathbf{X}\mathbf{X}\mathbf{A}$	18	-+-	(CURR_REMAINING_BA	CURR_REMAINING	
	19	3 SUM_REMAINING_BALANCE	SUM_REMAINING	STG_OPERATING		-//////////////////////////////////////	19	•••	(FISCAL_TIME_KEY	FISCAL_TIME_KEY	
	20	CURR_ADOPTED_BUDGET	CURR_ADOPTED_B	STG_OPERATING		////XXX\\\-	20	-+-	4	FISCAL_YEAR	FISCAL_YEAR	
	21	CURR_BUDGET_ADJUSTM	CURR_BUDGET_AD	STG_OPERATING		////X\\\\\	21	•••	4	FISCAL_PERIOD	FISCAL_PERIOD	
	22	CURR_YEAR_TO_DATE_A	CURR_YEAR_TO_D	STG_OPERATING		//////\\\\	22	-+-	4	FUND	FUND	
	23	CURR_ENCUMBRANCES	CURR_ENCUMBRA	STG_OPERATING		//// \\\4	23	•••	4	ORGANIZATION_CODE	ORGANIZATION_C	
	24	CURR_BUDGET_RESERVA	CURR_BUDGET_RE	STG_OPERATING		//// \\4	24	-+-		PROGRAM	PROGRAM	
	25	OURR_ACCUMULATED_B	CURR_ACCUMULAT	STG_OPERATING		V// \4	25	010	4	ACTIVITY	ACTIVITY	
	26	CURR_GRANT_ACTIVITY	CURR_GRANT_ACT	STG_OPERATING						-		
	27	() CURR_REMAINING_BALA	CURR_REMAINING	STG_OPERATING								

Figure 4.1: Source to Target mapping in SAS[®] DI Studio.

stg_operating_ledger_cunm using and ODS source table operating_ledger_cunm.

Within the extract transformation there is an option to filter the rows extracted according our needs. This operation is similar to 'select' used along with a 'where' condition in plain structured query language (SQL).

Loading a dimension table: Figure 4.3 shows how a dimension table in a data mart is loaded. The source table is year_type_definition from the ODS and the target dimension table is academic_calendar_dim. In the first step, some simple SQL is run which truncates the dimension table, then the next steps show data extraction from the source table based on some filter conditions mentioned in the extract transformation. The SCD type 1 transformation is then used to generate a value for time_key which is the surrogate key for the target table. This generates an integer incremented by 1 for each new record inserted into the table. The consequent

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Figure 4.2: Populating a staging table using SQL transformations in SAS[®] DI Studio.

steps show execution of SQL for some calculated or derived fields in the target table.



Loading a fact table: The fact table contains the foreign keys to the respective

Figure 4.3: Populating a dimension table.

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dimensions which is the reason why fact table needs to be loaded after all the dimension tables have been loaded. In Figure 4.4 an ETL job to populate a fact table is demonstrated. The target table is finance_fact. It can be noticed that the facts are coming from the staging table while the keys come from the dimension tables and are pulled using join or lookup transformations.

Joins and where conditions can be specified with in the DI studio, and Figure 4.5 shows such an example. Join types like left, right, full, inner. cross or union can be specified and clauses like where, group by, having, order by and sub-query can be given with in this GUI tool which makes complicated SQL easier to implement.

Generating a work flow in the DI studio is very intuitive. Once jobs are created, they can be run directly from the DI studio interface or can be deployed to a scheduling server. These jobs generate a '.sas' file which is the actual executable program run on the server. Once jobs are created in the DI studio, they are deployed to the scheduling server. Here a work flow is created and jobs are selected to run as part of the flow. In Figure 4.6 a complete flow of loading a star schema tables is shown. First all the staging tables are refreshed. When only all of them are successful, which is represented by the 'and' gate, the work flow moves on to the next jobs, which is to load the dimension tables. These jobs can also be run simultaneously, which can be seen in the comments 'start(index_dim)' which means the next job kicks off as soon as the current one starts. And finally the fact table is loaded after all dimension tables have been loaded seen as 'done(account_dim)' in the comments.

In DI studio, a work flow can be scheduled or run based on many conditions. Figure 4.7 shows the wide range of options available. It can be run manually any time, or it can be scheduled to run multiple times at specified points of time. Triggers can be programmed to run the flow at any time or file event including conditions like arrival of a file and increase in a file size.

The DI studio allows enough flexibility to run custom SAS code. This option is present in many transformations including execute, table-loader, splitter, datatransfer and surrogate-key-generator. Figure 4.8 shows a simple job containing an SQL extract transformation which contains SQL code wrapped around by proc-SQL which is a function used by SAS[®] to interpret SQL code. Figure 4.9 shows sample proc-SQL code. This code starts with a proc-SQL command. The option nosymbolgen specifies that log messages about macro variable references will not be displayed. Within the connect string, details like database, path which is defined in a SAS[®] library, user name and password are provided. The password can be encoded by using SAS[®] function called pwencode. The actual SQL statement is an execute statement. Control flow of transformations in a job in Figure 4.10 shows how order by which transformations are run can be changed by dragging them and placing them where desired. The control flow can then be validated with the press of a button. Job status shows progress of a job can be checked for any errors or warnings or successful completion at each stage or transformation. Figure 4.11 shows the status window in the DI studio GUI for the academic_calendar_dim job. The engine looks for any precode first and runs it if present and then follows through all the steps and checks for any postcode after the final step. Job statistics as shown in Figure 4.12 play an important role in optimization of jobs. It helps in understanding duration of each job, CPU time, memory occupied and threads on the server. Depending on the necessity, parameters in the job or on the server can be changed to allow more threads or more memory.

4.3 Refreshing the data mart

Currently SAS[®] scheduler within the management console is being used to schedule jobs and work flows depending on the refresh needs. There are two ways of refreshing

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the data mart tables. Complete reload and incremental load.

The refresh strategy for each table may vary depending on how the source table data is refreshed. For example, in the case of person dimension table, we have one record per person and any change in the detail, is replicated by replacing old data. In such a situation, it is better to opt for a complete reload, instead of tracking and updating changes. Even in the case of a fact table for instance, it is more practical to re-build it each time. This will ensure proper referential integrity of the fact table and that the keys are pointing back to the correct record in the dimension table.

However in the case of student or course dimensions, the data in the respective source tables in the ODS is not manipulated. Only new records are added to them. Therefore an incremental load process may suffice here.

Data mart maintenance is relatively easier and cheaper as compared to a 3NF database because of fewer number of tables involved. A proper naming convention was also followed when naming fact, dimension or staging tables and indexes.

4.4 ETL performance and data validation

The SAS[®] DI Studio was able to perform row inserts into Oracle tables at a rate of one million records per minute. This was achieved while running multiple jobs in parallel. After the data mart is populated, simple tests are run like record counts. More complex queries are also run to check performance and also data validation. Sample results are sent to business users for validation before moving jobs and data to production environment. After this stage, data is automatically refreshed by the time event or trigger events in the scheduling server.



Figure 4.4: Populating a fact table - Finance Fact.



Figure 4.5: Joins and where conditions in SAS[®] DI Studio.



Figure 4.6: Work flow, parallel jobs and scheduling in SAS[®] DI Studio.

Schedule Flow	
Choose the trigger(s) that will start the flow "finance_fact". Select Manage Using scheduling server (SAS Distributed In-Process Services Scheduling Se	e to create, edit, or delete triggers for this flow. rver), flows may be triggered by time events or file events defined here.
Run Now Manually to the scheduling server	
Select one or more triagers for this flow	
Available triggers	Selected triagers
Runs on: 12/1/13 at 16:20	Image: Manage
Grouping conditions	Triggers selected f
Run when any of the conditions occur	······································
Run only when all of the conditions occur	
	OK Cancel <u>H</u> elp

Figure 4.7: Job scheduling triggers in SAS[®] DI Studio.



Figure 4.8: SQL Extract transform to run custom SQL.

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```
□proc sql;
 options nosymbolgen;
    connect to oracle (user=unm oia staging
     password="{SAS002}B38A003D0E37DB4F3E619F7838AD52CD" PATH=odst);
 execute (
    DROP TABLE unm oia staging.STG ACADEMIC STUDY CUNM
 ) by oracle;
 execute (
 CREATE TABLE unm_oia_staging.STG_ACADEMIC_STUDY_CUNM
 ( Student Id,
    Person Uid,
    NAME,
    ACADEMIC YEAR,
    ACADEMIC_PERIOD, , , , . )
 AS SELECT id,
           person uid,
           name,
           academic year,
           academic period, , , , .
      FROM ODSMGR.ACADEMIC_STUDY_CUNM@OIA ODST ODSP.UNM.EDU
      WHERE ACADEMIC PERIOD >= '200680' ) by oracle;
    disconnect from oracle;
 quit;
```

Figure 4.9: Proc-SQL example to run custom queries.

Sta	tus	Warnings and Errors	Statistics Cont	rol Flow
*	1	n a 🖉 🖉 🖣		
#		Name	Туре	
1		sou Execute	Execute	
2		📑 Extract	Extract	
3		🚰 SCD Type 1	SCD Type 1	
4		sou etl_timestamp	Execute	
5		seu hed_regdate	Execute	
6		sou aid_year	Execute	
7		sou aid_year_desc	Execute	
8		sou calendar_year	Execute	

Figure 4.10: Control flow of transformations in a job.

Status Warning	s and Errors Statistics Contr	ol Flow
iii 🔒		
Order	Name	Status
1	Precode	Completed successfully
2	squ Execute	Completed successfully
3	📑 Extract	Completed successfully
4	SCD Type 1	Completed successfully
5	sel_timestamp	Completed successfully
6	se hed_regdate	Completed successfully
7	squ aid_year	Completed successfully
8	sou aid_year_desc	Completed successfully
9	sou calendar_year	Completed successfully
10	Postcode	Completed successfully
	🌼 academic_calendar_dim	Completed successfully

Figure 4.11: Job status.

Status Warnings and Errors Statistics Control Flow							
🛄 🖬 🛔 🏐 Kar Chart 🛛 🖾 👘 Kart Strength Science Content All transformations 🗸 👘 Kart Run: Dec 5, 2013 1:16:34 PM 🔯 Clear All							
Duration	CPU Time	Current Memory	System Memory	Current I/O	System I/O	Server	Threads
0.022	0.03	13721.6	12476.416	32	2520	bansasd	11
0.593	0.28	13983.744	12738.56	1264	3784	bansasd	11
0.819	0.31	0	12738.56	0	3784		11

Figure 4.12: Job statistics.

Chapter 5

Reporting from the data mart

5.1 Data Mart Performance

The data mart was designed and implemented using a dimensional modeling method namely star schema. A star schema is essentially easy to understand, implement and maintain. As seen in the previous chapters, a star schema has a fact table and a few dimension tables. The student data mart has several subject areas like student enrollment, course enrollment, admissions, financial aid and so on. Each subject areas has a fact table with dimension tables shared between these multiple subject areas. Such tables are called conformed dimensions. For example the student enrollment star schema has one fact table student_enrollment_fact and dimension tables like academic_calendar_dim, student_dim, course_dim etc.. The naming convention has been chosen in such a way that it is apparent as to what data is present in that table. A dimension table contains comprehensive information about that aspect of the subject area. For example, course_dim table contains all information regarding a course like college, department, course reference number, academic period in which it was offered, section number and so on. The fact table contains transaction level

data capturing all events regarding that subject area.

As each subject area is defined and the tables designed, it becomes very clear as to what tables need to be used for a given query to that subject area. Reports can be generated very easily based on a proper understanding of the data mart structure.

A fact table may contain many records, but because it contains a very small number of columns querying the fact table is much faster. This is one of the main reasons why the data mart should be able to perform better than the ODS in response to report generation requests. More reasons are mentioned below.

Logical design: The star schema design requires fewer number of joins to build a report as compared to the number of joins required to build the same report from ODS tables.

Indexing appropriate columns: Columns in the tables of this star schema are indexed optimally according the query or report requirements. Whereas in ODS, the tables if they are indexed it is not done optimally. Also most of the time, views rather than tables in ODS are used to build reports by most users at UNM, which are slower to access.

Using surrogate keys: We use just this one numerical field to join a fact and a dimension table as compared to using multiple fields to join tables in ODS. For instance, when querying course level statistics, the fact table used is course_enrollment_fact which is joined to dimension table academic_calendar_dim on time_key and to course_dim on course_key. Time_key and course_key are numerical fields generated by the ETL job having unique values for each record in a dimension table.

Using summary fact tables: In reports which require the use of aggregate functions, summary fact tables are built with the aggregate fields pre-populated so that the reports can directly read from these tables avoiding calculations on-the-fly

Chapter 5. Reporting from the data mart



Figure 5.1: Average ODS versus data mart performance.

thus ensuring faster delivery of reports.

I received response the times for the SQL queries against both ODS and the data mart. These queries were based the grade distribution report and also a few other reports which gives grade distributions and pass rates for courses, section, ethnicity. Figure 5.1 shows an averaged performance of data mart versus ODS over different queries. The data mart performed better than the ODS. On an average, the data mart is more than 50% faster than the ODS.

5.2 Reports

The purpose building a data mart using star schema is to enable the development of a wide variety of reports and predictive analytics. This is possible because of

the flexible way in which the data is organized. It is the same data as in ODS but organized in a different, more logical way. It is also relatively easy to develop reports out of the data mart as compared to ODS because of the fewer number of tables involved.

Several specific reports were proposed to be generated for a project based on this student mart. Some have been built while others are still in development. Below is a non-exhaustive description of a few of them. The WebFOCUS reporting tool is being used to generate these reports.

General ad-hoc class performance report: For a given semester, this report allows one to get grade distributions, withdrawal rates and pass rates for selected courses and sections. Courses can be selected by instructor, course reference number, or by selecting a series of courses and sections. This report will also need to have the ability to restrict its output to various sub-populations based on ethnicity, financial aid, or other demographic conditions. Inputs can be course reference number, instructor, academic period, subject code, course number, section number, ethnicity, financial aid status, category of financial aid received, status as a first generation college student (if possible) Outputs are grade distribution, withdrawal rate and pass rate. As an example of demonstrating the simplicity of building a report from the data mart, in this report, dimension tables used are course_dim, academic_calendar_dim, student_dim and the fact table used is course_enrollment_fact joined on the surrogate keys time_key, student_key and course_key. Therefore with relatively simple SQL joins and select operations, this complex report was built enabling drill-down and drill-across capabilities which allow dynamic reporting based on selecting academic period, department, course and section.

Two course grade comparison report: This report will compare how students in one course during one semester performed in another course during a subsequent semester (e.g. Physics I during Fall of 2012 and Physics II during Spring of

2013). This report will also be able to look at sub-populations in a similar manner as the previous report.

A few other reports that are supported by the data mart are mentioned below:

- A report that shows the transitions to and the transitions from a given major. For a given time period, it shows the number and majors of students that transferred into a given major. Also for a given time period, it shows the number and majors of students who transferred from a given major.
- A report that gives the percentage of STEM classes taken by STEM majors, broken down by major for a given academic period.
- A report that gives the number of degrees granted, broken down by major and level of degree including average GPA for a given semester.
- A report that gives the number and percentage of non-STEM majors in STEM courses broken down by course.

Figure 5.2 is a report which shows student credit hours (sch) generated by faculty in each academic period by college. The report in Figure 5.3 shows student enrolled hours in an academic period by college and by course level, i.e., lower undergraduate, upper undergraduate or graduate.

ACADEMIC_PERIOD_DESC: COLLEGE_CODE_DESC: Spring 2011 Anderson Schools of Management					
Run Reset Save Clear Output Run in a new window					
			Level		
			Lower	Upper	Grad
College	Rank	Instructor Name			
Anderson Schools of Management	Assistant Professor	Last, Hite		123	123
		Mahto, Rajankumar V		207	
		McNiright, Reed		267	105
		Montoya, Manuel		300	
		Morales-Camargo, Emmanuel		36	60
		Patterson, Karen		81	57
		Taylor, Scott		102	135
	Associate Professor	Berman, Shawn	1.1	222	81

Figure 5.2: SCH generated by faculty by academic period, college.

Academic_Period: Campus Spring 2008 Main	: •	lun		
		Course L	evel.	
		Lower	Upper	Graduate
College	Department			
Anderson Schools of Management ASM	Anderson Schools of Management ASM	1,248	12,304	3,814
Subtotal: Anderson Schools of Mana	gement ASM	1,248	12,304	3,814
Associate VP Student Services	Air Force ROTC	71	70	
	Army ROTC	86	151	
	Naval ROTC	21	81	
Subtotal: Associate VP Student Servi	ices	178	302	
College of Arts Sciences A S	*Interdisciplinary: A.S.	99	891	47
	African American Studies	99	177	
	American Studies Department	1,146	954	290

Figure 5.3: Student hours enrolled by academic period, college.

Chapter 6

Future Work

The student data mart being discussed in this thesis currently has a star schema that incorporates fact tables for applications and admissions, student enrollment, course enrollment, semester performance and financial aid. In the near future, we also look to incorporate curriculum data, student assessment data, career services and alumni data. Having this kind of data from high school GPA and admission test scores, academic performance at UNM and how well students are able to move onto a job or higher studies helps us to better understand and measure student success.

A finance data mart is also being built to analyze the flow of money through various organizations for various activities. The finance reports and applications for the president's and the provost's office as well as individual departments will be supported by this data mart.

In the near future, the University of New Mexico plans to build a research space data mart which will have information about the research space allotted to each principal investigator bringing in funding to UNM. This data mart includes the investigator data, research proposal, grant, fund, organization, program, account and activity data. It would also contain the space data which includes what space

was allotted to which researcher and how it was used during a certain period of time. This data mart would give UNM scope to do analytics on how efficiently space is being used on campus, improve space allotment and also predict future usage.

The ETL process will be automated further to support nightly updates of the data mart and automatic report generation and publication. There is scope to take leverage of the built-in transformations in the SAS[®] data integration studio to support dimensional modeling, handle many-to-many relationships and slowly changing dimensions. Apart from that it includes top of the line tools which will help build interesting analytic models including forecasting, what-if analysis and predictive analytic models. Reports will be built using SAS[®] visual analytics (VA).

Sankey diagrams shown below were developed as a part of another analytics initiative and are currently run on Amazon EC2 cloud with a Postgres database as the back end. The data was loaded into this database using Excel spreadsheets. In future, these Sankey diagrams will be supported by the data marts.

The Sankey diagrams can be viewed at www.provostcloud.unm.edu. The first example shown in Figure 6.1 is the college flow of majors by semester in 2008, Arts and Sciences college, Chemistry department. There are a bunch of filters and statistics provided at the bottom of the page to drill down to the user's needs. The second sankey diagram in Figure 6.2 highlights part of the flow when one of the nodes is hovered upon by the mouse. This uses Data-Driven Documents (D3) Javascript programming. At the bottom of the web page there are some filters and the corresponding statistics displayed. This is shown in Figure 6.3.



Figure 6.1: Sankey Diagram for 2008 Arts and Sciences Chemistry College Flow.



Chapter 6. Future Work

51 Figure 6.2: Sankey Diagram node highlight example.



Select year: 2008 V
Select college: AS 🔻
Select major: CHEM (Chemistry)
Gender: 🔻
ACT: Min: 1 🔻 Max: 36 🔻
SAT: Min: 400 ▼ Max: 2400 ▼
Ipeds: Hispanic 🔹

	Semester						
Year grad rate							
Туре	semester 1	semester 2	semester 3	semester 4	semester 5	semester 6	total
STOP	0 (0.0%)	2 (6.1%)	2 (6.1%)	0 (0.0%)	2 (6.1%)	2 (6.1%)	2
STOP_OUTSIDE	0 (0.0%)	0 (0.0%)	0 (0.0%)	2 (6.1%)	3 (9.1%)	3 (9.1%)	3
AS_CHEM	0	1	3	2	5	7	7
AS_NON_CHEM	1	1	2	4	4	9	9
UC_CHEM	13	13	8	8	3	2	2
UC_NON_CHEM	17	15	14	13	10	5	5
OUTSIDE	2	1	4	4	6	5	5
GRAD_OUTSIDE	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0
GRAD	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0

Figure 6.3: Sankey diagram statistics display.

Appendices

(

6.1 Student data mart table structure (DDL)

The table structure of the student data mart designed, implemented and in production environment, is given below.

CREATE TABLE ACADEMIC_CALENDAR_DIM

TIME_KEY	NUMBER,
ACADEMIC_PERIOD	VARCHAR2(63 CHAR),
ACADEMIC_PERIOD_DESC	VARCHAR2(255 CHAR),
ACADEMIC_YEAR	VARCHAR2(63 CHAR),
ACADEMIC_YEAR_DESC	VARCHAR2(255 CHAR),
SEMESTER_START	DATE,
SEMESTER_END	DATE,
AID_YEAR	VARCHAR2(63 CHAR),
AID_YEAR_DESC	VARCHAR2(255 CHAR),
CALENDAR_YEAR	NUMBER(4),
HED_REGDATE	VARCHAR2(5 CHAR),
ACASEM	VARCHAR2(30 CHAR),
ETL_TIMESTAMP	TIMESTAMP(6)

);

CREATE TABLE COURSE_DIM

(

COURSE_KEY ACADEMIC_PERIOD ACADEMIC_PERIOD_DESC SUB_ACADEMIC_PERIOD SUB_ACADEMIC_PERIOD_DESC COURSE_REFERENCE_NUMBER SUBJECT_CODE SUBJECT_CODE_DESC COURSE_NUMBER SECTION_NUMBER COURSE_TITLE_SHORT COURSE_STATUS_CODE COURSE_STATUS_CODE_DESC CAMPUS CODE CAMPUS_CODE_DESC COLLEGE_CODE COLLEGE_CODE_DESC DEPARTMENT_CODE DEPARTMENT_CODE_DESC GENERATED_CREDITS MIN_CREDIT_HRS MAX_CREDIT_HRS MIN_BILLING_HRS MAX_BILLING_HRS

NUMBER, VARCHAR2(64 CHAR), VARCHAR2(255 CHAR), VARCHAR2(12 CHAR),VARCHAR2(50 CHAR),VARCHAR2(5 CHAR), VARCHAR2(4 CHAR), VARCHAR2(30 CHAR), VARCHAR2(5 CHAR), VARCHAR2(3 CHAR), VARCHAR2(30 CHAR), VARCHAR2(63 CHAR),VARCHAR2(255 CHAR), VARCHAR2(63 CHAR), VARCHAR2(255 CHAR),VARCHAR2(63 CHAR), VARCHAR2(255 CHAR), VARCHAR2(63 CHAR), VARCHAR2(255 CHAR), NUMBER(9,3), NUMBER(7,3), NUMBER(7,3), NUMBER(7,3), NUMBER(7,3),

SCHEDULE_TYPE	VARCHAR2(3 CHAR),
SCHEDULE_TYPE_DESC	VARCHAR2(30 CHAR),
INSTRUCTIONAL_METHOD_CODE	$VARCHAR2(8 \ CHAR) ,$
INSTRUCTIONAL_METHOD_CODE_DESC	VARCHAR2(255 CHAR),
INTEGRATION_CODE	VARCHAR2(5 CHAR),
SESSION_ID	$VARCHAR2(8 \ CHAR) ,$
COURSELEVEL	$VARCHAR2(2 \ CHAR) ,$
COURSE_LEVEL_DESC	VARCHAR2(120 CHAR),
CROSS_LIST_GROUP_CODE	$VARCHAR2(2 \ CHAR) ,$
ACTUAL ENROLLMENT	NUMBER(4),
PREV_ENROLLMENT	NUMBER(4),
COURSE_FEES	NUMBER(12,2),
COURSE_START_DATE	DATE,
COURSE_END_DATE	DATE,
CENSUS_ENROLLMENT_DATE1	DATE,
CENSUS_ENROLLMENT1	NUMBER(4),
CENUS_ENROLLMENT_DATE2	DATE,
CENSUS_ENROLLMENT2	NUMBER(4),
EFFECTIVE_START_DATE	DATE,
EFFECTIVE_END_DATE	DATE,
GRADE_TYPE	CHAR(20 CHAR),
GRADE_TYPE_DESC	CHAR(40 CHAR),
ACTIVE_FLAG	NUMBER,
ETL_TIMESTAMP	TIMESTAMP(6)

);

CREATE TABLE COURSE_ENROLLMENT_FACT

(

TIME_KEY	NUMBER,
COURSE_KEY	NUMBER,
DEPARTMENT_KEY	NUMBER,
INSTRUCTOR_GROUP_KEY	NUMBER,
CROSS_LIST_GROUP_CODE	VARCHAR2(2 CHAR),
TOTALENROLLMENT	NUMBER,
A_PLUS_COUNT	NUMBER,
A_COUNT	NUMBER,
A_MINUS_COUNT	NUMBER,
B_PLUS_COUNT	NUMBER,
B_COUNT	NUMBER,
B_MINUS_COUNT	NUMBER,
C_PLUS_COUNT	NUMBER,
C_COUNT	NUMBER,
C_MINUS_COUNT	NUMBER,
D_PLUS_COUNT	NUMBER,
D_COUNT	NUMBER,
D_MINUS_COUNT	NUMBER,
F_COUNT	NUMBER,
CR_COUNT	NUMBER,
NR_COUNT	NUMBER,
NC_COUNT	NUMBER,
W_COUNT	NUMBER,
WP_COUNT	NUMBER,
WF_COUNT	NUMBER,
WNC_COUNT	NUMBER,
W_TOTAL_COUNT	NUMBER,
AUD_COUNT	NUMBER,

WHITE_COUNT	NUMBER,
AFRICAN_AMERICAN_COUNT	NUMBER,
AMERICAN_INDIAN_COUNT	NUMBER,
HISPANIC_COUNT	NUMBER,
ASIAN_COUNT	NUMBER,
NATIVE_HAWAIIAN_COUNT	NUMBER,
TWO_MORE_RACES_COUNT	NUMBER,
RACE_ETHN_UNKOWN_COUNT	NUMBER,
NON_RES_COUNT	NUMBER,
ETL_TIMESTAMP	TIMESTAMP(6)

);

CREATE TABLE DEGREESAWARDED_FACT

(
l		

TIME_KEY	NUMBER,
STUDENT_KEY	NUMBER,
PERSON_KEY	NUMBER,
PERSON_UID	NUMBER,
STUDENT_ID	$VARCHAR2(9 \ CHAR),$
DEGREE_CODE	VARCHAR2(63 CHAR),
DEGREE_CODE_DESC	VARCHAR2(255 CHAR),
AWARD_CATEGORY	VARCHAR2(63 CHAR),
AWARD_CATEGORY_DESC	VARCHAR2(255 CHAR),
STATUS_CODE	VARCHAR2(63 CHAR),
STATUS_CODE_DESC	VARCHAR2(255 CHAR),
OUTCOME_AWARDED_IND	$VARCHAR2(1 \ CHAR) ,$
GRADUATED_IND	$VARCHAR2(1 \ CHAR) ,$
TRANSFER_WORK_EXISTS_IND	$VARCHAR2(1 \ CHAR) ,$

OUTCOME_GRADUATION_DATE	DATE,
ACADEMIC_PERIOD	VARCHAR2(63 CHAR),
ACADEMIC_PERIOD_GRADUATION	VARCHAR2(63 CHAR),
GRADUATION_STATUS	$VARCHAR2(3 \ CHAR) ,$
GRADUATION_STATUS_DESC	VARCHAR2(255 CHAR),
CREDITS_ATTEMPED	NUMBER,
CREDITS_EARNED	NUMBER,
GPA_CREDITS	NUMBER,
QUALITY_POINTS	NUMBER,
CREDITS_PASSED	NUMBER,
GPA	NUMBER,
ETL_TIMESTAMP	TIMESTAMP(6)

);

CREATE TABLE DEPARTMENT_DIM

(

DEPARTMENT_KEY	NUMBER,
DEPARTMENT_CODE	VARCHAR2(63 CHAR),
DEPARTMENT_CODE_DESC	VARCHAR2(255 CHAR),
COLLEGE_CODE	VARCHAR2(63 CHAR),
COLLEGE_CODE_DESC	VARCHAR2(255 CHAR),
CAMPUS_CODE	$V\!ARCH\!AR2(63\ C\!H\!AR),$
CAMPUS_CODE_DESC	VARCHAR2(255 CHAR),
ORGANIZATION_LEVEL_2	$V\!ARCH\!AR2(63\ C\!H\!AR),$
ORGANIZATION_DESC_2	VARCHAR2(255 CHAR),
ETL_TIMESTAMP	TIMESTAMP(6)

);
CREATE TABLE FINANCIAL_AID_FACT

(

TIME_KEY	NUMBER,
STUDENT_KEY	NUMBER,
FINANCIAL_AID_KEY	NUMBER,
STUDENT_ID	VARCHAR2(9 CHAR),
PERSON_UID	NUMBER,
AID_YEAR	VARCHAR2(63 CHAR),
CAMPUS_CODE	VARCHAR2(63 CHAR),
AID_YEAR_DESC	VARCHAR2(255 CHAR),
AWARD_STATUS	VARCHAR2(63 CHAR),
AWARD_STATUS_DESC	VARCHAR2(255 CHAR),
AWARD_STATUS_DATE	DATE,
AWARD_OFFER_IND	VARCHAR2(63 CHAR),
AWARD_ACCEPT_IND	VARCHAR2(63 CHAR),
AWARD_DECLINE_IND	VARCHAR2(63 CHAR),
AWARD_CANCEL_IND	VARCHAR2(63 CHAR),
AWARD_OFFER_AMOUNT	NUMBER,
AWARD_ACCEPT_AMOUNT	NUMBER,
AWARD_PAID_AMOUNT	NUMBER,
PELL_GRANT_RECEIVED_FLAG	NUMBER,
PELL_ELIGIBLE_FLAG	NUMBER,
ETL_TIMESTAMP	TIMESTAMP(6)

);

CREATE TABLE FINANCIAL_AID_FUND_DIM (

FINANCIAL_AID_FUND_KEY NUMBER,

AID_YEAR	$V\!ARCH\!AR2(63\ CH\!AR),$
AID_YEAR_DESC	VARCHAR2(255 CHAR),
FUND	VARCHAR2(63 CHAR),
FUND_TITLE	VARCHAR2(255 CHAR),
FUND_SOURCE	VARCHAR2(63 CHAR),
FUND_SOURCE_DESC	VARCHAR2(255 CHAR),
FUND_TYPE_CODE	VARCHAR2(63 CHAR),
FUND_TYPE_DESC	VARCHAR2(255 CHAR),
GIFT_OR_SELF_HELP_AID	VARCHAR2(63 CHAR),
GIFT_OR_SELF_HELP_AID_DESC	VARCHAR2(255 CHAR),
FUND_DETAIL_CODE	VARCHAR2(63 CHAR),
FEDERAL_FUND_ID	VARCHAR2(63 CHAR),
ETL_TIMESTAMP	TIMESTAMP(6)

);

CREATE TABLE INSTRUCTIONAL_ASSIGNMENT_FACT

(
	TIME_KEY	NUMBER,
	INSTRUCTOR_KEY	NUMBER,
	COURSE KEY	NUMBER,
	SUB_ACADEMIC_PERIOD	VARCHAR2(63 CHAR),
	SUB_ACADEMIC_PERIOD_DESC	VARCHAR2(255 CHAR),
	CATEGORY	$VARCHAR2(2 \ CHAR) ,$
	PRIMARY_IND	$VARCHAR2(1 \ CHAR) ,$
	PERCENT_RESPONSIBILITY	NUMBER,
	SESSION_PERCENTAGE	NUMBER

);

CREATE TABLE INSTRUCTOR DIM

(

INSTRUCTOR_KEY	NUMBER,
INSTRUCTOR_ID	VARCHAR2(9 CHAR),
INSTRUCTOR_UID	NUMBER,
INSTRUCTOR_FIRST_NAME	VARCHAR2(60 CHAR),
INSTRUCTOR_LAST_NAME	VARCHAR2(60 CHAR),
INSTRUCTOR_RANK_CODE	VARCHAR2(63 CHAR),
INSTRUCTOR_RANK_CODE_DESC	VARCHAR2(255 CHAR),
INSTRUCTOR_BASE_SALARY	CHAR(20 CHAR),
PRIM_APPOINTMENT_DESC	VARCHAR2(30 CHAR),
PRIM_APPOINTMENT_DEPT_CODE	VARCHAR2(4 CHAR),
PRIM_APPT_DEPT_DESC	VARCHAR2(30 CHAR),
PRIM_EFFECTIVE_START_DT	DATE,
PRIM_EFFECTIVE_END_DT	DATE,
ACADEMIC_TITLE	CHAR(20 CHAR),
PRIM_TENURE_CODE	VARCHAR2(2 CHAR),
PRIM_TENURE_DEPT_CODE	VARCHAR2(4 CHAR),
PRIM_TENURE_EFF_DATE	DATE,
PRIM_TENURE_TRACK_BEGIN_DATE	DATE,
PRIM_TENURE_REVIEW_DATE	DATE,
SEC_APPOINTMENT_DESC	VARCHAR2(30 CHAR),
SEC_APPOINTMENT_DEPT_CODE	VARCHAR2(30 CHAR),
SEC_APPT_DEPT_DESC	VARCHAR2(30 CHAR),
SEC_TENURE_CODE	VARCHAR2(2 CHAR),
SEC_TENURE_DEPT_CODE	VARCHAR2(4 CHAR),
SEC_TENURE_EFF_DATE	DATE,
SEC_TENURE_TRACK_BEGIN_DATE	DATE,

SEC_TENURE_REVIEW_DATE	DATE,
RANK_EFFECTIVE_START_DT	DATE,
RANK_EFFECTIVE_END_DT	DATE,
ACTIVE_FLAG	NUMBER,
EFFECTIVE_START_DATE	DATE,
EFFECTIVE_END_DATE	DATE,
ETL_TIMESTAMP	TIMESTAMP(6)

);

(

CREATE TABLE MAJOR.DEPT.XWALK

MAJOR_CODE VARCHAR2(10 CHAR), MAJOR_DESCRIPTION VARCHAR2(31 CHAR), ORGANIZATION_LEVEL_5 VARCHAR2(7 CHAR), ORGANIZATION_DESC_5 VARCHAR2(34 CHAR), VARCHAR2(8 CHAR), OBSOLETE BANNER_MAJOR_CODE VARCHAR2(10 CHAR), BANNER_ORG_CODE VARCHAR2(15 CHAR), ORGANIZATION_LEVEL_3 VARCHAR2(7 CHAR), ORGANIZATION_DESC_3 VARCHAR2(34 CHAR), ORGANIZATION_LEVEL_2 VARCHAR2(7 CHAR), VARCHAR2(25 CHAR) ORGANIZAITON_DESC_2

);

(

CREATE TABLE PERSON_DIM

PERSON_KEY PERSON_ID

NUMBER, VARCHAR2(9 CHAR),

PERSON_UID NUMBER, FIRST NAME VARCHAR2(63 CHAR), LAST_NAME VARCHAR2(63 CHAR), MIDDLE_INITIAL VARCHAR2(15 CHAR), MIDDLE_NAME VARCHAR2(63 CHAR), VARCHAR2(20 CHAR), NAME_SUFFIX FULL_NAME_FMIL VARCHAR2(255 CHAR), FULL_NAME_LFMI VARCHAR2(255 CHAR), NETID VARCHAR2(30 CHAR), GENDER VARCHAR2(63 CHAR), GENDER_DESC VARCHAR2(63 CHAR), BIRTH_DATE DATE, CURRENT_AGE NUMBER, DECEASED STATUS VARCHAR2(1 CHAR), DECEASED DATE DATE, CONFIDENTIALITY_IND VARCHAR2(1 CHAR), PRIMARY_ETHNICITY VARCHAR2(63 CHAR), PRIMARY_ETHNICITY_DESC VARCHAR2(255 CHAR), PRIM_ETHNICITY_CATEGORY VARCHAR2(63 CHAR),PRIM_ETHNICITY_CATEGORY_DESC VARCHAR2(255 CHAR), HISPANIC_LATINO_ETHNICITY_IND VARCHAR2(1 CHAR), IPEDS_VALUES NUMBER, IPEDS_VALUES_DESC VARCHAR2(63 CHAR), HISPANIC NUMBER, AMERICAN_INDIAN NUMBER, ASIAN NUMBER, AFRICAN_AMERICAN NUMBER, NATIVE_HAWAIIAN NUMBER,

WHITE	NUMBER,
NON_RESIDENT_ALIEN	NUMBER,
RACE_CATEGORY_COUNT	NUMBER,
RACE_COUNT	NUMBER,
RACE_ETHNICITY_CONFIRM_IND	VARCHAR2(1 CHAR),
RACE_ETHNICITY_CONFIRM_DATE	DATE,
CITIZENSHIP_TYPE	VARCHAR2(63 CHAR),
CITIZENSHIP_TYPE_DESC	VARCHAR2(255 CHAR),
CITIZENSHIP_IND	$VARCHAR2(1 \ CHAR) ,$
NATION_OF_CITIZENSHIP	VARCHAR2(63 CHAR),
NATION_OF_CITIZENSHIP_DESC	VARCHAR2(255 CHAR),
VISA_TYPE	VARCHAR2(63 CHAR),
VISA_TYPE_DESC	VARCHAR2(255 CHAR),
VETERAN_CATEGORY	$VARCHAR2(1 \ CHAR) ,$
VETERAN_CATEGORY_DESC	VARCHAR2(45 CHAR),
VETERAN_SPECIAL_DISABLED_IND	$VARCHAR2(1 \ CHAR) ,$
MILITARY_SEPARATION_DATE	DATE,
MA_ADDRESS_TYPE	VARCHAR2(2 CHAR),
MA_ADDRESS_TYPE_DESC	VARCHAR2(50 CHAR),
MA_ACTIVE_ADDRESS_IND	VARCHAR2(2 CHAR),
MA_STREET_LINE1	VARCHAR2(100 CHAR),
MA_STREET_LINE2	VARCHAR2(100 CHAR),
MA_STREET_LINE3	VARCHAR2(100 CHAR),
MA_CITY	VARCHAR2(63 CHAR),
MA_STATE_PROVINCE	$VARCHAR2(3 \ CHAR) ,$
MA_STATE_PROVINCE_DESC	VARCHAR2(35 CHAR),
MA_POSTAL_CODE	VARCHAR2(30 CHAR),
MA_COUNTY_CODE	VARCHAR2(6 CHAR),

MA_COUNTY_CODE_DESC MA_NATION_CODE MA_NATION_CODE_DESC ADDRESS_COUNT PHONE_NUMBER_COMBINED PHONE TYPE PHONE DESC PHONE_COUNT EMAIL ADDRESS EMAIL_TYPE EMAIL_TYPE_DESC EMAIL_COMMENT EMAIL_PREFERRED_ADDRESS PE ADDRESS TYPE PE ADDRESS TYPE DESC PE_ACTIVE_ADDRESS_IND PE_STREET_LINE1 PE_STREET_LINE2 PE_STREET_LINE3 PE_CITY PE_STATE_PROVINCE PE_STATE_PROVINCE_DESC PE_POSTAL_CODE PE_COUNTY_CODE PE_COUNTY_CODE_DESC PE_NATION_CODE PE_NATION_CODE_DESC EFFECTIVE_START_DATE

VARCHAR2(20 CHAR),VARCHAR2(5 CHAR), VARCHAR2(50 CHAR),NUMBER, VARCHAR2(35 CHAR), VARCHAR2(5 CHAR), VARCHAR2(50 CHAR),NUMBER, VARCHAR2(255 CHAR), VARCHAR2(35 CHAR),VARCHAR2(255 CHAR), VARCHAR2(255 CHAR), VARCHAR2(255 CHAR), VARCHAR2(63 CHAR), VARCHAR2(255 CHAR), VARCHAR2(2 CHAR), VARCHAR2(255 CHAR),VARCHAR2(255 CHAR),VARCHAR2(255 CHAR),VARCHAR2(63 CHAR), VARCHAR2(63 CHAR), VARCHAR2(255 CHAR), VARCHAR2(63 CHAR), VARCHAR2(63 CHAR), VARCHAR2(255 CHAR), VARCHAR2(63 CHAR), VARCHAR2(255 CHAR), DATE,

EFFECTIVE_END_DATE	DATE,
SSN	VARCHAR2(63 CHAR),
STARS_ID	VARCHAR2(50 CHAR),
ACTIVE_FLAG	NUMBER,
ETL_TIMESTAMP	TIMESTAMP(6)

);

CREATE TABLE PROGRAM.DIM

(
l		

PROGRAM_KEY	INTEGER,
PROGRAM_CODE	VARCHAR2(12 CHAR),
PROGRAM.DESC	VARCHAR2(30 CHAR),
LEVEL_CODE	VARCHAR2(2 CHAR),
CAMPUS_CODE	$VARCHAR2(3 \ CHAR) ,$
COLLEGE_CODE	$VARCHAR2(2 \ CHAR) ,$
DEGC_CODE	VARCHAR2(6 CHAR),
ETL_TIMESTAMP	DATE

);

CREATE TABLE PROGRAM_ENROLLMENT_FACT

(
l	

TIME_KEY	NUMBER,
PROGRAM.KEY	NUMBER,
TOTAL ENROLLMENT	NUMBER,
WHITE_COUNT	NUMBER,
AFRICAN_AMERICAN_COUNT	NUMBER,
AMERICAN_INDIAN_COUNT	NUMBER,
HISPANIC_COUNT	NUMBER,

ASIAN_COUNT	NUMBER,
NATIVE_HAWAIIAN_COUNT	NUMBER,
TWO_MORE_RACES_COUNT	NUMBER,
RACE_ETHN_UNKOWN_COUNT	NUMBER,
NON_RES_COUNT	NUMBER,
ETL_TIMESTAMP	DATE

);

(

CREATE TABLE STUDENT_DIM

STUDENT_KEY NUMBER, STUDENT_ID VARCHAR2(15 CHAR), PERSON_UID NUMBER, ACADEMIC_PERIOD VARCHAR2(30 CHAR), ACADEMIC_PERIOD_DESC VARCHAR2(30 CHAR), PROGRAMLCODE VARCHAR2(12 CHAR), PROGRAM_CODE_DESC VARCHAR2(30 CHAR), PRIMARY_PROGRAM_IND VARCHAR2(1 CHAR), YEAR_ADMITTED VARCHAR2(4 CHAR), YEAR_ADMITTED_DESC VARCHAR2(20 CHAR), AGE_ADMITTED NUMBER, CATALOG_ACADEMIC_PERIOD VARCHAR2(6 CHAR), CATALOG_ACADEMIC_PERIOD_DESC VARCHAR2(30 CHAR), AWARD CATEGORY VARCHAR2(2 CHAR), AWARD_CATEGORY_DESC VARCHAR2(30 CHAR), NEW_STUDENT_IND VARCHAR2(1 CHAR), ADMISSIONS_POPULATION VARCHAR2(2 CHAR), ADMISSIONS_POPULATION_DESC VARCHAR2(30 CHAR), DEGREE_CODE VARCHAR2(6 CHAR), DEGREE_CODE_DESC VARCHAR2(30 CHAR), FIRST_MAJOR_CODE VARCHAR2(4 CHAR), FIRST_MAJOR_CODE_DESC VARCHAR2(30 CHAR), FIRST_MAJOR_CIP_CODE VARCHAR2(6 CHAR), FIRST_MAJOR_CIP_DESC VARCHAR2(30 CHAR),FIRST_MAJOR_CONC1 VARCHAR2(4 CHAR), FIRST_MAJOR_CONC1_DESC VARCHAR2(30 CHAR),VARCHAR2(4 CHAR), FIRST_MAJOR_CONC2 FIRST_MAJOR_CONC2_DESC VARCHAR2(30 CHAR),FIRST_MAJOR_CONC3 VARCHAR2(4 CHAR), FIRST_MAJOR_CONC3_DESC VARCHAR2(30 CHAR), FIRST_MAJOR_DEPT_CODE VARCHAR2(4 CHAR), FIRST_MAJOR_DEPT_CODE_DESC VARCHAR2(30 CHAR),FIRST_MAJOR_COLLEGE_CODE VARCHAR2(2 CHAR), FIRST_MAJOR_COLLEGE_CODE_DESC VARCHAR2(30 CHAR),FIRST_MAJOR_CAMPUS_CODE VARCHAR2(3 CHAR), FIRST_MAJOR_CAMPUS_CODE DESC VARCHAR2(30 CHAR),SECOND_MAJOR_CODE VARCHAR2(4 CHAR), SECOND_MAJOR_DESC VARCHAR2(30 CHAR),SECOND_MAJOR_CIP_CODE VARCHAR2(6 CHAR), SECOND_MAJOR_CIP_DESC VARCHAR2(30 CHAR), SECOND_MAJOR_CONC1 VARCHAR2(4 CHAR), SECOND_MAJOR_CONC1_DESC VARCHAR2(30 CHAR), SECOND_MAJOR_CONC2 VARCHAR2(4 CHAR), SECOND_MAJOR_CONC2_DESC VARCHAR2(30 CHAR),SECOND_MAJOR_CONC3 VARCHAR2(4 CHAR), VARCHAR2(30 CHAR), SECOND_MAJOR_CONC3_DESC

SECOND_MAJOR_DEPT_CODE VARCHAR2(4 CHAR), SECOND_MAJOR_DEPT_CODE_DESC VARCHAR2(30 CHAR), FIRST_MINOR_CODE VARCHAR2(4 CHAR), FIRST_MINOR_CODE_DESC VARCHAR2(30 CHAR), SECOND_MINOR_CODE VARCHAR2(4 CHAR), SECOND_MINOR_CODE_DESC VARCHAR2(30 CHAR),STUDENT_STATUS_CODE VARCHAR2(2 CHAR), STUDENT_STATUS_CODE_DESC VARCHAR2(10 CHAR), CURRENT_TIME_STATUS_CODE VARCHAR2(2 CHAR), CURRENT_TIME_STATUS_CODE_DESC VARCHAR2(30 CHAR), STUDENT_CLASS_BOAP_CODE VARCHAR2(2 CHAR), STUDENT_CLASS_BOAP_CODE_DESC VARCHAR2(30 CHAR), STUDENT_CLASSIFICATION VARCHAR2(2 CHAR), STUDENT_CLASSIFICATION_DESC VARCHAR2(30 CHAR),STUDENT_LEVEL_CODE VARCHAR2(2 CHAR), STUDENT_LEVEL_CODE_DESC VARCHAR2(30 CHAR),RESIDENCY_CODE VARCHAR2(2 CHAR), RESIDENCY_DESC VARCHAR2(30 CHAR),RESIDENCY_IND VARCHAR2(1 CHAR), FINANCIAL_AID_ELIGIBLE_FLAG NUMBER, FINANCIAL_AID_RECEIVED_FLAG NUMBER, FINAID_APPLICANT_IND VARCHAR2(1 CHAR), STUDENT_RATE_CODE VARCHAR2(2 CHAR), STUDENT_RATE_CODE_DESC VARCHAR2(21 CHAR), STUDENT_ATTRIBUTE_CODE VARCHAR2(63 CHAR), STUDENT_ATTRIBUTE_CODE_DESC VARCHAR2(255 CHAR), ENROLLED_IND VARCHAR2(1 CHAR), VARCHAR2(1 CHAR), **REGISTERED_IND**

REGISTERED_ABQ	VARCHAR2(1 CHAR),
REGISTERED_LOS_ALAMOS	$VARCHAR2(1 \ CHAR) ,$
REGISTERED_TAOS	$VARCHAR2(1 \ CHAR) ,$
REGISTERED_GALLUP	$VARCHAR2(1 \ CHAR) ,$
REGISTERED_VALENCIA	$VARCHAR2(1 \ CHAR) ,$
EFFECTIVE_START_DATE	DATE,
EFFECTIVE_END_DATE	DATE,
STUDENT_POPULATION	$VARCHAR2(1 \ CHAR) ,$
STUDENT_POPULATION_DESC	VARCHAR2(30 CHAR),
ACTIVE_FLAG	NUMBER,
ETL_TIMESTAMP	TIMESTAMP(6)

);

CREATE TABLE STUDENT_ENROLLMENT_FACT

(
l		

TIME_KEY	NUMBER,
STUDENT_KEY	NUMBER,
PERSON_KEY	NUMBER,
COURSE_KEY	NUMBER,
PROGRAMKEY	NUMBER,
INSTRUCTOR_GROUP_KEY	NUMBER,
STUDENT_ID	$VARCHAR2(9 \ CHAR) ,$
CREDIT_HRS_ATTEMPTED	NUMBER,
CREDIT_HRS_EARNED	NUMBER,
COURSE_CREDITS	NUMBER,
FINAL_GRADE_RECEIVED	VARCHAR2(63 CHAR) ,
GRADE_POINTS_RECEIVED	NUMBER,
REGISTRATION_STATUS	VARCHAR2(63 CHAR),

	REGISTRATION_STATUS_DESC	VARCHAR2(255 CHAR),
	COMPLETED_FLAG	NUMBER,
	ETL_TIMESTAMP	TIMESTAMP(6)
)	;	

CREATE TABLE STUDENT_LEVEL_SUMMARY_FACT

(
	PERSON_KEY	NUMBER,
	STUDENT_ID	VARCHAR2(9 CHAR),
	PERSON_UID	NUMBER,
	NAME	VARCHAR2(255 CHAR),
	NO_OF_COURSES_ENROLLED	NUMBER,
	GPA_TYPE	$VARCHAR2(1 \ CHAR) ,$
	GPA_TYPE_DESC	$VARCHAR2(11 \ CHAR) ,$
	ACADEMIC_STUDY_VALUE	VARCHAR2(63 CHAR),
	ACADEMIC_STUDY_VALUE_DESC	VARCHAR2(255 CHAR),
	GPA	NUMBER,
	GPA_CREDITS	NUMBER,
	CREDITS_ATTEMPTED	NUMBER,
	CREDITS_EARNED	NUMBER,
	CREDITS_PASSED	NUMBER,
	QUALITY_POINTS	NUMBER,
	ETL_TIMESTAMP	TIMESTAMP(6)
`		

);

(

CREATE TABLE STUDENT_TERM_SUMMARY_FACT

TIME_KEY	NUMBER.

PERSON_KEY	NUMBER,
STUDENT KEY	NUMBER,
ACADEMIC_PERIOD	VARCHAR2(6 CHAR),
STUDENT_ID	VARCHAR2(9 CHAR),
PERSON_UID	NUMBER,
NO_OF_COURSES_ENROLLED	NUMBER,
GPA_TYPE	$VARCHAR2(1 \ CHAR) ,$
GPA_TYPE_DESC	$VARCHAR2(11 \ CHAR) ,$
ACADEMIC_STUDY_VALUE	VARCHAR2(63 CHAR),
ACADEMIC_STUDY_VALUE_DESC	VARCHAR2(255 CHAR),
GPA	NUMBER,
GPA_CREDITS	NUMBER,
CREDITS_ATTEMPTED	NUMBER,
CREDITS_EARNED	NUMBER,
CREDITS_PASSED	NUMBER,
QUALITY_POINTS	NUMBER,
ETL_TIMESTAMP	TIMESTAMP(6)

);

References

- [1] R. Kimball and M. Ross. The Data Warehouse Toolkit. *The definitive guide to dimensional modeling*.
- [2] W. H. Inmon. Building the Data Warehouse. *Getting Started*.
- [3] R. Kimball and J. Caserta. The Data Warehouse ETL Toolkit. *Practical Techniques for Extracting, Cleaning, Conforming, and Delivering data.*
- [4] R. Kimball and M. Ross. The Kimball Group Reader. *Releatlessly Practical Tools for Data Warehousing and Business Intelligence.*
- [5] T. Teorey, S. Lightstone and T.Nadeau. Database Modeling and Design. Logical Design.
- [6] C. Adamson. Star Schema. The complete reference.
- [7] SAS Institute Inc.. SAS[®] Data Integration Studio 4.7 User Guide 2013.