D4M: Bringing Associative Arrays to Database Engines

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Abstract—The ability to collect and analyze large amounts of data is a growing problem within the scientific community. The growing gap between data and users calls for innovative tools that address the challenges faced by big data volume, velocity and variety. Numerous tools exist that allow users to store, query and index these massive quantities of data. Each storage or database engine comes with the promise of dealing with complex data. Scientists and engineers who wish to use these systems often quickly find that there is no single technology that offers a panacea to the complexity of information. When using multiple technologies, however, there is significant trouble in designing the movement of information between storage and database engines to support an end-to-end application along with a steep learning curve associated with learning the nuances of each underlying technology. In this article, we present the Dynamic Distributed Dimensional Data Model (D4M) as a potential tool to unify database and storage engine operations. Previous articles on D4M have showcased the ability of D4M to interact with the popular NoSQL Accumulo database. Recently however, D4M now operates on a variety of backend storage or database engines while providing a federated look to the end user through the use of associative arrays. In order to showcase how new databases may be supported by D4M, we describe the process of building the D4M-SciDB connector and present performance of this connection.

Keywords—Big Data, Data Analytics, Dimensional Analysis, Federated Databases

I. INTRODUCTION

The challenges associated with big data are commonly referred to as the 3 V’s of Big Data - Volume, Velocity and Variety [1]. The 3 V’s provide a guide to the largest outstanding challenges associated with working with big data systems. Big data volume stresses the storage, memory and compute capacity of a computing system and requires access to a computing cloud. The velocity of big data stresses the rate at which data can be absorbed and meaningful answers produced. Big data variety makes it difficult to develop algorithms and tools that can address that large variety of input data.

The ability to collect and analyze large amounts of data is a growing problem within the scientific community. The growing gap between data and users calls for innovative tools that address the challenges faced by big data volume, velocity and variety. Numerous tools exist that allow users to store, query and index these massive quantities of data. Each storage or database engine comes with the promise of dealing with complex data. Scientists and engineers who wish to use these systems often quickly find that there is no single technology that offers a panacea to the complexity of information [2, 3]. When using multiple technologies, however, there is significant trouble in designing the movement of information between storage and database engines to support an end-to-end application. In this article, we present the Dynamic Distributed Dimensional Data Model - a technology developed at MIT Lincoln Laboratory. Previous articles on D4M [4, 5] have showcased the ability of D4M to interact with the popular Apache Accumulo database. Recent advances in D4M now allow D4M to operate on a variety of back end storage or database engines while providing a federated look to the end user through the use of associative arrays. Associative arrays provide a mathematical interface across different database technologies and can help solve one of the largest problems of working with numerous backend storage or database engines - how do we correlate information that may be spread across different storage or database engines?

The Intel Science and Technology Center (ISTC) on Big Data [6] is centered at the MIT Lincoln Laboratory and supports five major research themes: Big Data Databases and Analytics, Big Data Math and Algorithms, Big Data Visualization, Big Data Architectures, and Streaming Big Data. One of the core goals of the ISTC is to develop the next generation software stack required to manage heterogenous data in order to enable large scale data analytics on data from the Internet of Things (IoT). This solution stack is known as the Big Data Working Group (BigDAWG) stack [7]. The BigDAWG solution stack is a vertically integrated stack that supports numerous hardware platforms, analytics libraries, database and storage engines, software development through the Big Dawg Query Language (BQL) and Compiler, visualization and presentation of data through a variety of applications. The BQL will provide software and analytics developers an abstraction of the underlying database and storage engines, analytics libraries and hardware platforms. A key feature of BQL is to develop the API required to provide a federated look to developers.

Federated databases have the ability to abstract away details about the underlying storage or database engine. Very often, federated databases are used to provide some mutual benefit. This feature can be quite appealing to scientists who wish to write complex analytics and are not necessarily database or storage experts. There has been much promise of federated
databases \[8\]. Federated databases provide the ability to give users the feel of a data warehouse without physically moving data into a central repository \[9\]. As an example of a federated database, consider Myria \[10\] \[11\], a distributed database that uses SQL or Myria, as the language all of which was developed at the University of Washington. One of the challenges in database federation has been in developing a programming API that can be used to interact with the ever-increasing variety of databases and storage engines \[12\].

D4M’s mathematical foundation, associative arrays, have the ability to help alleviate the challenges associated with open problems in federated database. Having a one-to-one relationship with triple store or with key-value store systems allows a flexible representation that can be supported by many databases. The ability to perform linear algebraic operations on associative arrays (and thus data stored in different database engines) opens up big-data analytics to non-computer scientists. We believe that an API based on mathematical operations is easy to learn. The software implementation in popular languages such as MATLAB, Octave, and Julia allows the rapid prototyping of new and complex analytics with minimal effort.

In this article, we present our work on developing associative arrays as the datatype for big data in Section \[II\]. In Section \[III\] we present D4M and provide examples of how database operations such as context and cast can be done with D4M and associative arrays through the D4M MATLAB toolbox. In Section \[IV\] in order to motivate the ease at which new database support can be built into D4M, we detail the D4M-SciDB connector. In order to demonstrate the use of D4M, associative arrays, and database engines, we provide a simple case study of developing an analytic for medical data that spans across three different storage engines in Section \[V\]. Finally, we conclude in Section \[VI\].

II. ASSOCIATIVE ARRAYS

Associative arrays are used to describe the relationship between multidimensional entities using numeric/string keys and numeric/string values. Associative arrays provide a generalization of sparse matrices. Formally, an associative array \(A\) is a map from \(d\) sets of keys \(K_1 \times K_2 \times ... \times K_d\) to a value set \(V\) with a semi-ring structure

\[
A : K_1 \times K_2 \times ... \times K_d \rightarrow V
\]

where \((V, \oplus, \otimes, 0, 1)\) is a semi-ring with addition operator \(\oplus\), multiplication operator \(\otimes\), additive-identity/multiplicative-annihilator 0, and multiplicative-identity 1. Furthermore, associative arrays have a finite number of non-zero values which means their support \(\text{supp}(A) = A^{-1}(V \setminus \{0\})\) is finite. While associative arrays can be any number of dimensions, a common technique to use associative arrays in databases is to project the \(d\)-dimensional set into two dimensions as in:

\[
A : K_1 \times \{K_2 \cup K_3 \cup ... \cup K_d\} \rightarrow V
\]

where the \(\cup\) operation indicates a union operation. In this 2D representation, \(K_1\) is often referred to as the row key and \(\{K_2 \cup K_3 \cup ... \cup K_d\}\) is referred to as the column key.

As a data structure, associative arrays return a value given some number of keys and constitute a function between a set of tuples and a value space. In practice, every associative array can be created from an empty associative array by simply adding and subtracting values. With this definition, it is assumed that only a finite number of tuples will have values, and all other tuples have a default value of the additive-identity/multiplicative-annihilator 0. Further, the associative array mapping should support operations that resemble operations on ordinary vectors and matrices such as matrix multiplication. In practice, associative arrays support a variety of linear algebraic operations such as summation, union, intersection, multiplication and element wise operations. Summation of two associative arrays, for example, that do not have any common row or column key performs a union of their underlying non-zero keys. Element wise multiplication as an example performs an operation similar to an intersection. Associative arrays have a one-to-one relationship with key-value store or triple store databases, sparse matrices, and adjacency or incidence matrix representations of graphs. These relations allow complex datasets to be easily converted to associative array representation. Linear algebraic operations on associative arrays can be used to perform graph algorithms as described in \[13\].

NoSQL database tables can be exactly described using the mathematics of associative arrays \[14\]. In the D4M schema, a table in a NoSQL database, such as Apache Accumulo, is an associative array. In this context, the primary differences between associative arrays and sparse matrices are: associative array entries always carry their global row and column labels while sparse matrices do not. Another difference between associative arrays is that sparse matrices can have empty rows or columns while associative arrays do not.

Using associative arrays as a datatype for big data has many benefits such as:

- Using associative arrays as the base datatype will make database development easier. DB developers will only need to provide an optimized interface to associative arrays;
- Associative arrays can limit the programming language-DB connectors that are required. Currently, if there are \(N\) programming languages and \(M\) database engines, we need \(N \times M\) connectors. Having a single interface can reduce this to \(N + M\) connectors; and
- An API based on mathematical operations is natural for the vast majority of scientists and engineers.

III. THE DYNAMIC DISTRIBUTED DIMENSIONAL DATA MODEL (D4M)

The Dynamic Distributed Dimensional Data Model (D4M) combines techniques from diverse fields to support rapid prototyping of big data problems in a familiar programming environment. Specifically, D4M consists of 3 components:

- A software API that enables D4M to connect with databases,
- A software API that supports Associative Arrays and their mathematics, and
- A schema to represent unstructured multi-dimensional datasets.

D4M has a multi layer architecture that allows users to develop analytics without knowledge of the underlying engine. In Figure \[1\] we describe the various components of D4M. The D4M software API is roughly broken into two components - a client binding and a server binding.
The D4M client binding is responsible for most of the sophisticated data processing. Support for the associative array datatype allows users to quickly convert a representative subset of their dataset into an associative array and prototype different algorithms to test for mathematical correctness. Given the relationship between associative arrays and sparse matrices, there are a wide variety of potentially complex algorithms such as machine learning that can be directly translated to operations on associative arrays. Once algorithms have been developed and tested for correctness, a user can make use of the D4M server binding to scale their dataset by connecting to a database engine.

The D4M server binding allows users to map their in-memory associative arrays to a wide variety of backend storage or database engines. Creating a database server binding creates an object in local memory that contains information about the database type, authentication information, and host. Using this object, one can create a table object that binds the D4M client to a DB table. With minimal effort, a user can read in raw data, convert to associative array representation, and insert into a database. Querying from the database results in associative arrays that can be directly used for the complex analytics developed using the client binding. Syntax wise, querying data from an associative array or database binding is the same. For example, suppose we have an associative array \( A \) and database table binding \( T \), finding all data that has a row key between \( a \) and \( d \) is denoted as: \( A(a : d,:) \) or \( T(a : d,:) \) depending on whether information is being requested from the associative array or database table. In both cases, the data returned is in the form of an associative array.

In order to connect to different database engines, D4M uses various connectors (either existing or custom built) to connect to popular databases. As an example, the D4M-mysql connection is done by calling the Java Database Connector (JDBC) from D4M. While the current implementation of D4M has a limited set of backend engines that are supported, this number is increasing.

A typical user workflow to develop an analytic on a large dataset will be as follows. First, the user makes use of a schema to convert their raw dataset (often in JSON, TSV, CSV format) into an associative array. The user can then read a one or more associative arrays into memory and develop the desired analytic. The user can verify correctness of analytic with alternate pieces of the larger dataset. The user can then insert the full dataset, converted to associative array format, into a database engine (or set of databases). The user can then query for data which results in an associative array that can be used directly in the analytic developed.

One of the challenges in working with numerous backend databases is in developing a uniform syntax and data format to put queries in the context of a particular database or to cast information from one to another in order to perform cross-DB analytics.

The Context operation is to provide explicit control of the backend database or storage engine. The Cast operator is to move data between storage and database engines.

In D4M, the context operation is done by using the DBserver command which returns a DB object that contains information about the specific database being connected to. Thus, when performing a query on a backend database, the DB operator will use the correct context and connector to perform the required query. The DBserver function in the server binding returns an object to a DB that contains the host, instance, and authentication information.

```matlab
DB = DBserver(host,type,instanceName,user,pass)
```

**Inputs:**
- `host` = database host name
- `type` = type of database
- `instanceName` = database instance name
- `username` = username in database
- `password` = password associated with username

**Outputs:**
- `DB` = database object with a binding to specific DB

Once a DB object is created, one can perform database specific operations such as `ls` or create a binding to a specific table in the database. If the requested table does not exist, a table with that name will be created in the database. Binding to a table provides functionality such as querying and inserting data.

```matlab
A = T(rows,cols)
```

**Inputs:**
- `T` = database table
- `rows` = row keys to select
- `cols` = column keys to select

**Outputs:**
- `A` = associative array of all non-empty row/columns

The following example describes how one can connect to a database and return all the information in a particular table in the database.

```matlab
DB = DBserver('host','type','db_name','user','pass')
table_list = ls(DB); % returns all tables in DB
T = DB('tab_name'); % Table binding to tab_name
A = T(:,:); % Entries of tab_name put in assoc array
```
In D4M, associative arrays can be used as the interface to cast information from one database to another. Consider the following example of casting data from mySQL to Apache Accumulo (a noSQL database). Of course, it is up to the user to ensure that data can be cast from one database to another (for example, certain databases may not support certain datatypes or schemas). The following example describes how one could cast data from mySQL to a noSQL database such as Apache Accumulo via associative arrays.

```matlab
DBsql=DBserver('host','mysql', 'sql_dbname','u','p');
DBnosql=DBserver('host','nosql', 'dbname','u','p');
T=DBsql('tabname'); % Tabname in sql_dbname
Asql=T(:,:); % Entries of tabname into Asql
Tnosql=DBnosql('tabname'); % Tabname dbname
put(Tnosql, Asql); %Insert into tabname in dbname
Anosql=Tnosql(:,:); %Entries of tabname into Anosql
```

One of the important aspects of D4M is the ability to easily add new database engines via an API exposed by the database developer. In the next section, we will discuss how a popular NewSQL database SciDB was added to D4M. A thorough description of the D4M-Accumulo binding can be found in [4].

IV. THE SCI DB-D4M CONNECTION

SciDB is a parallel database designed for multidimensional data management with support for a variety of in-database computation and analytics. SciDB has the ability to connect to a variety of client side tools such as R, Python or a Web Browser. The SciDB coordinator is responsible for moving data across back end data storage [15]. Connection to a SciDB server is mediated via the coordinator. Other instances in the SciDB cluster are referred to as worker nodes. SciDB represents data as multidimensional arrays which are defined by specifying dimensions and attributes. Dimensions are 64-bit integers, and attributes can be one of many supported SciDB datatypes. SciDB supports a variety of connection mechanisms such as JDBC or a SHIM.

A SHIM is a small library that is capable of intercepting API calls and translating them in to the underlying system API. In SciDB, the Shim is a basic SciDB client that exposes SciDB functionality via a HTTP interface [16]. The D4M-SciDB connection is built using the SciDB SHIM. Specifically, given an operation on SciDB table, D4M will convert this operation into a query that is supported by the SciDB SHIM and pass it to the coordinator node. The coordinator node will then perform the requested operation and return data back to D4M via the established SHIM connection. As described in Figure 2, when a user calls a SciDB context function, D4M will automatically translate the query into an operation supported by the SciDB SHIM. When connecting to a SciDB table, a user will first call the `DBserver` operation that will authenticate and connect to SciDB via the SHIM. This will return a token that is held in an object returned by `DBserver`. To establish a connection with an existing table in SciDB, one can issue the D4M `DTable` command, that takes as an argument the object returned by `DBserver` and the required dimensions and attributes. Currently, a number of D4M server binding commands are supported to directly interface with the SciDB table. For example, `nnz`, will return the number of non-zero entries in a table. In any of these API examples, the command issues the query to the backend database using the context of the DB command. Consider the example of inserting an associative array into SciDB. The user will create an associative array and table binding as described in Section III. The user can use the D4M `put` command which converts the associative array into a datatype supported by SciDB and ingests this converted data to the SciDB coordinator node. The dataflow is described in Figure 2.

After optimization, inserts are done in 128 MB batches and using the parallel CSV loader. Once data is in SciDB, the standard D4M API can be used to pull data back. For example, if the table binding is held in the object `T`, `T(row1:rowN,:)` returns all the elements in the table, and `T(row1:rowN,:)` returns the elements within the row range `row1:rowN`.

A. D4M-SciDB Performance

In order to benchmark SciDB, data was generated using a random graph generator from the Graph500 benchmark [17]. The Graph500 scalable data generator that can efficiently generate power-law graphs that represent common graphs such as those generated from social media datasets. The number of vertices and edges in the graph are set using a positive integer called the SCALE parameter. Given a SCALE parameter, the number of vertices, N, and the number of edges, M, are then computed as \( N = 2^{\text{SCALE}} \), and \( M = 8N \).

For example, if SCALE = 14, then N = 16384 and M = 131072. The Graph500 generator uses a recursive matrix algorithm [18] to generate a set of starting vertices and ending vertices corresponding to edges in a graph. This graph is then be represented as a large \( N \times N \) sparse matrix A, where \( A(i,j) = 1 \) indicates an edge from vertex i to vertex j, often called the adjacency matrix. As an example, consider Figure 3 which shows the adjacency matrix and distribution of degrees for a SCALE 14 graph generated using the Kronecker graph generator. The degree of a vertex is the number of edges incident to a vertex. For a power law graph, we expect to see an exponential increase when looking at the number of nodes with particular degrees (i.e., few nodes will have a high degree, and many nodes will have a low degree).

SciDB is a highly scalable database and is capable of connecting with multiple clients at once. In order to test the scalability of SciDB, we use pMATLAB [19] in addition to D4M to insert data from multiple clients simultaneously. In order to overcome a SciDB bottleneck that applies a table lock...
when data is being written to a table, we use D4M to create multiple tables based on the total number of ingestors. For example, if there are four simultaneous ingestors, we create 4 tables into which each ingestor will simultaneously insert. The resulting tables can be merged after the ingest using D4M if desired.

SciDB was launched using the MIT SuperCloud [20] architecture through the database hosting system. For the purpose of benchmarking SciDB on a single node, instances were launched on a system with Intel Xeon E5 processors with 16 cores and 64GB of RAM. SciDB coordinator and worker nodes were located on the same physical node.

Weak scaling is a measure of the time taken for a single processing element to solve a specific problem or fixed problem size per processor. In Figure 4, we describe the performance of SciDB in inserting Kronecker Graph whose SCALE varies with the number of processors into SciDB using D4M. The maximum performance (insert rate) was observed at 10 processors.

Strong scaling is a measure of the time taken for solving a fixed total problem size. Figure 5 describes the results varying the number of inserters for a fixed SCALE=19 Kronecker Graph. The maximum performance (insert rate) was observed to be at 8 processors.

V. MEDICAL BIG DATA PROCESSING WITH BIG DATA

Medical big data is a common example used to justify the adage that “one size does not fit all” for database and storage engines. Consider the popular MIMIC II dataset [21]. This dataset consists of data collected from a variety of Intensive Care Units (ICU) at the Beth Isreal Deaconess Hospital. The data contained in the MIMIC II dataset was collected over seven years and contains data from a variety of clinical and waveform sources. The clinical dataset contains the data collected from tens of thousands of individuals and consists of information such as patient demographics, medications, interventions, and text-based doctor or nurse notes. The waveform dataset contains thousands of time series physiological signal recordings such as ECG signals, arterial blood pressure, and other measurements of patient vital signs. In order to support data extraction from these different datasets, one option would be to attempt to organize all the information into a single database engine. However, existing technologies would prove to be cumbersome or inefficient for such a task. The next solution is to store and index each of the individual components into a storage or database engine that is the most efficient for a particular data modality. While technically this solution may be the most efficient, it makes application development difficult as researchers need to be aware of underlying technologies and make development highly dependent on changing technologies. D4M and associative arrays can be used to provide developers (such as a medical researcher) with an abstraction that hides such details in order to develop technology-agnostic applications. As a part of the ISTC for Big Data, a prototype application was developed that leverages different backend storage engines. In this solution, the MIMIC II clinical data was placed in a relational database (MySQL), the text notes were placed in Apache Accumulo, and the waveform data was placed in SciDB using D4M.

The prototype developed supports cross-database analytics such as: “tell me about what happens to heart rate variance of patients who have taken a particular medication.” Naturally, such a query needs information from the clinical data contained in MySQL database, the patient database contained in Accumulo and the waveform data contained in SciDB. The sample query provided is then be broken up into three distinct queries where: 1) tell me which patients have taken a particular medication goes to MySQL, 2) tell me which of these patients have heart beat waveforms goes to Accumulo,
and 3) show me what happened to these patients heart rate
variance goes to the waveform database. At each of these sub-
queries, associative arrays are generated that can be used to
move the results of one query to the next database engine.
In Figure 6, we show the web front end that uses D4M and
associative arrays to implement the query described above.
As an example of how D4M and associative arrays are used,
querying the relational table results in an associative array
where the row keys represent the table name, and column keys
represent the patients who have taken Lisinopril. The resulting
column keys are directly passed into Accumulo to find all
patients who have a certain type of waveform where the rows
contain the patient ID and columns contain related waveform
IDs. The resultant associative array can then be passed directly
into SciDB to extract the waveforms of interest and perform
the required analytic.

VI. CONCLUSIONS

D4M is a toolkit that supports a variety of database and
storage engine operations. Support for associative arrays can
be used as a natural interface between heterogenous database
engines. Currently, D4M is designed to work with a variety
of engines such as SQL, Accumulo, and SciDB. Currently,
the number of context operations is limited; however, D4M
exposes these operations to the user with context specific
operations by allowing pass-through queries. Further, casting
data from one engine to another requires data to pass through
the client which may be a bottleneck for large scale data
movement.

In this paper, we described D4M and the relation between
D4M, associative arrays and databases. D4M can be used as
a tool by application developers to write applications agnostic
of underlying storage and database engines. Current research
includes determining how data can be cast directly between
databases and increasing the number of context agnostic D4M
commands.

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