Big Data Bench 2.0

User's Manual

Contents

This document presents information on BigDataBench----a big data benchmark suite from web search engines, including a brief introduction and the usage of it. The information and specifications contained are for researchers who are interested in big data benchmarking.

Publishing information:
Release 2.0
Date 10/7/2013
Contact information:
Website: http://prof.ict.ac.cn/BigDataBench/

1 Background

BigDataBench is a big data benchmark suite from web search engines. Now, we provide the second release of BigDataBench for downloading. In this edition, we pay attention to big data workloads in three important applications domains in Internet services: search engine, social networks, and electronic commerce according to a widely acceptable metrics—the number of page views and daily visitors. The second release (BigDataBench 2.0) has 6 categories and 19 types' big data applications which are the most important domain in Internet services. It also provides an innovative data generation tool to generate scalable volumes of big data from a small-scale of real data preserving semantics and locality of the real data. The data sets in BigDataBench are generated by the tool. Users can also combine other applications in BigDataBench according to their own requirements.

2 Introduction of Big Data Bench 2.0

2.1 Our Benchmarking Methodology

The philosophy of BigDataBench methodology is From Real System to Real System. We widely investigate the typical Internet applications domains, then characterize the big data benchmark from two aspects: data sets and workloads. The methodology of our benchmark is shown in Figure1. First of all, we investigate the application category of Internet services, and choose the dominant application domains for further characterizing based on the number of page views. According to the analysis in [], the top three application domains hold 80% page views of all the Internet service. They are adopted in the BigDataBench application domain, which include search engine, social networks and electronic commerce. These domains represent the typical applications of Internet service, and the applications represent a wide range of categories to access the big data benchmarking requirement of workload diversity.

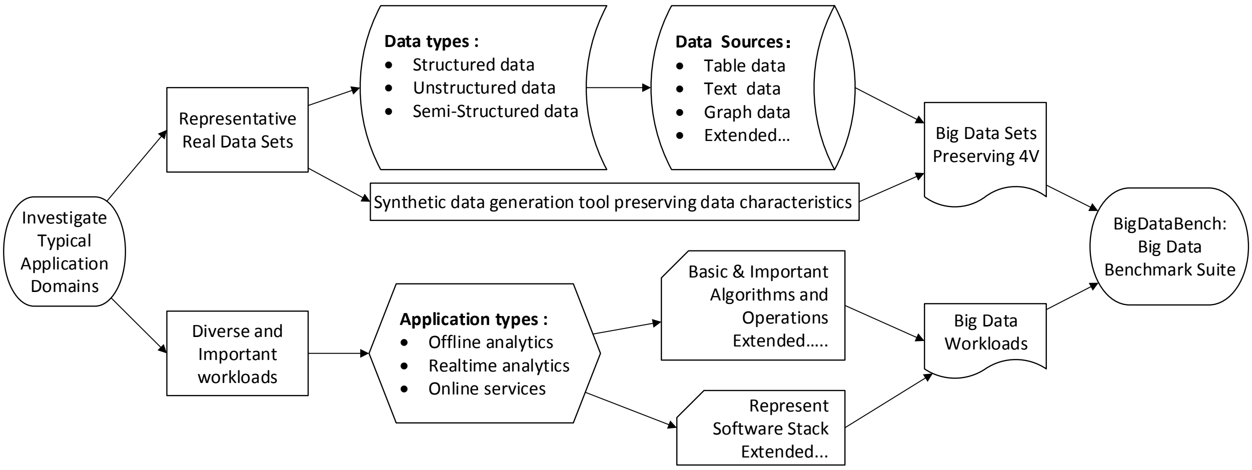

Figure1. BigDataBench Methodology

After choosing the application domains, we characterize the data sets and workloads of BigDataBench based on the requirements proposed in the next subsection.

2.2 Chosen Data sets and Workloads

As analyzed in our article, the data sets should cover different data types of big data applications. Based on the investigation of three application domains, we collect six representative real data sets. Table 2 shows the characteristics of six real data sets and their corresponding workloads and Table 3 shows the Diversity of data sets. The original data is real, however, not big. We need to scale the volume of the data while keep the veracity.

Table 2: The summary of six real data sets

No.	data sets	data size
1	Wikipedia Entries	4,300,000 English articles
2	Amazon Movie Reviews	7,911,684 reviews
3	Google Web Graph	875713 nodes, 5105039 edges
4	Facebook Social Network	4039 nodes, 88234 edges
5	ABC Transection Data	table1:4 columns, 38658 rows. table2:6 columns, 242735 rows
6	Profsearch person Resumes	278956 resumes

Table3.Data Diversity

Real data set	Data type	Application domains	Data source
Wikipedia Entries	un-structured	Search engine	text data
Amazon Movie Reviews	semi-structure	e-commence	text data
Google Web Graph	un-structured	Search engine	graph data
Facebook Social Graph	un-structured	social network	graph data
ABC Transaction Data	structured	e-commence	table data
Profsearch Person Resume	semi-structured	Search engine	table data

Further, we choose three different application domains to build our benchmark, because they cover the most general big data workloads.

For search engine, the typical workloads are Web Serving, Index and PageRank. For web applications, Web Serving is a necessary function module to provide an entrance for the service. Index is also an important module, which is widely used to speed up the document searching efficiency. PageRank is an important part to rank the searching results for search engines.

For ecommerce system, the typical workloads include Web Serving and Off-line Data Analysis. The Web Serving workload shows information of products and provides a convenient platform for users to buy or sell products. Off-line Data Analysis workload mainly does the data mining calculation to promote the buy rate of products. In BigDataBench we select these Data Analysis workloads: Collaborate Filtering and Baye.

For social networking service, the typical workloads are Web Serving and graph operations. The Web Serving workload aims to interactive with each user and show proper contents. Graph operations are series of calculations upon graph data. In BigDataBench, we use Kmeans and breath first search to construct the workloads of graph operation.

Besides, we defined three operation sets: Micro Benchmarks (sort, grep, word count and BFS), Database Basic Datastore Operations(read/write/scan) and Relational Query(scan/aggregation/join) to provide more workload choices.

Table 6: The Summary of BigDataBench.
(Benchmark i-(1,..,j) means 1th,..,j-th implementation of Benchmark i, respectively.)

Application Scenarios	Operations Algorithm	Data Type	Data Source	Software Stack	Application Type	Benchmark ID
Micro Benchmarks	Sort	Unstructured	Text	MapReduce, Spark, MPI	Offline Analytics	1-(1,2,3)
	Grep	Unstructured	Text	MapReduce, Spark, MPI	Offline Analytics	2-(1,2,3)
	WordCount	Unstructured	Text	MapReduce, Spark, MPI	Offline Analytics	3-(1,2,3)
	BFS	Unstructured	Graph	MapReduce, Spark, MPI	Offline Analytics	4-(1,2,3)
Basic Datastore Operations ("Cloud OLTP"	Read	Semi-structured	Table	Hbase, Cassandra, MongoDB, MySQL	Online Service	5-(1,2,3,4)
	Write	Semi-structured	Table	Hbase, Cassandra, MongoDB, MySQL	Online Services	6-(1,2,3,4)
	Scan	Semi-structured	Table	Hbase, Cassandra, MongoDB, MySQL	Online Services	7-(1,2,3,4)
Relational Query	Select Query	Structured	Table	Impala, Shark, MySQL, Hive	Realtime Analytics	8-(1,2,3,4)
	Aggregate Query	Structured	Table	Impala, Shark, MySQL, Hive	Realtime Analytics	9-(1,2,3,4)
	Join Query	Structured	Table	Impala, Shark, MySQL, Hive	Realtime Analytics	10-(1,2,3,4)
Search Engine	Nutch Server	Structured	Table	Hadoop	Online Services	11
	PageRank	Unstructured	Graph	Hadoop, MPI, Spark	Offline Analytics	12-(1,2,3)
	Index	Unstructured	Text	Hadoop, MPI, Spark	Offline Analytics	13-(1,2,3)
Social Network	Olio Server	Structured	Table	MySQL	Online Service	14
	Kmeans	Unstructured	Graph	Hadoop, MPI, Spark	Offline Analytics	15-(1,2,3)
	Connected Components	Unstructured	Graph	Hadoop, MPI, Spark	Offline Analytics	16-(1,2,3)
E-commerce	Rubis Server	Structured	Table	MySQL	Online Service	17
	Collaborative Filtering	Unstructured	Text	Hadoop, MPI, Spark	Offline Analytics	18-(1,2,3)
	Naive Bayes	Unstructrued	Text	Hadoop, MPI, Spark	Offline Analytics	19-(1,2,3)

By choosing different operations and environment, it's possible for users to compose specified benchmarks to test for specified purposes. For example basic applications under MapReduce environment can be chosen to test if a type of architecture is proper for doing MapReduce jobs.

2.3 Use case

This subsection will describe the application example of BigDataBench.

General procedures of using BigDataBench are as follows:

1. Choose the proper workloads. Select workloads with the specified purpose, for example basic operations in Hadoop environment or typical search engine workloads.

2. Prepare the environment for the corresponding workloads. Before running the experiments, the environment should be prepared first for example the Hadoop environment.

3. Prepare the needed data for workloads. Generally, it's necessary to generate data for the experiments with the data generation tools.

4. Run the corresponding applications. With all preparations done, it's needed to start the workload applications and/or performance monitoring tools in this step.

5. Collect results of the experiments.

Here we provide two usage case to show how to use our benchmark to achieve differnet evaluating task.

Case one: from the perspective of maintainer of web site

If application scene and software are known, the maintainer want to choose suitable hardware facilities. For example, someone have develop a web site of search engine, and use Hadoop, Hive, Hbase as their infrastructures. Now he want evaluate if specifical hardware facilities are suitable for his scene using our benchmark. First, he should select the workloads of search engine, saying search web serving, indexing, and pagerank.

Also, the basic operations like sort, wordcount, and grep should be contained. To covering the Hive and Hbase workload, he also should select the hive queries and read, write, scan of Hbase. Next, he should prepare the environment and corresponding data. Finally, he runs each workloads selected and observe the resluts to make evaluation.

Case two: fromm the perspective of architechturer

Supose that someone is planning to design a new machine for common big data usage. It is not enough to run subset of the workloads, since he doesn't know what special application scene and soft stack the new machine is used for. The comprehensive evaluation is needed, so that he should run every workload to reflect the performance of different application scene, program frawork, ddata warehouse, and NoSQL database. Only in this way, he can say his new design is indeed beneficial for big data usage.

Other use cases of BigDataBench include:

Web serving applications:
Using BigDataBench to study the architecture feature of Web Serving applications in big data scenario(Search Engine).

Data Analysis workload's feature:
Another kind of use case is to observe the typical data analysis workloads'(for example PageRank, Recommendation) architectural characters.

Different storage system:
In BigDataBench, we also provide different data management systems(for example hbase, Cassandra, hive). Users can choose one or some of them to observe the architectural feature by running the basic operations(sort, grep, wordcount).

Different programing models:
Users can use BigDataBench to study three different programing models: MPI, MapReduce and Spark.

3 Prerequisite Software Packages

Software	Version	Download
Hadoop	1.0.2	http://hadoop.apache.org/#Download+Hadoop
HBase	0.94.5	http://www.apache.org/dyn/closer.cgi/hbase/
Cassandra	1.2.3	http://cassandra.apache.org/download/
MongoDB	2.4.1	http://www.mongodb.org/downloads
Mahout	0.8	https://cwiki.apache.org/confluence/display/MAHOUT/Downloads
Hive	0.9.0	https://cwiki.apache.org/confluence/display/Hive/GettingStarted #GettingStarted-InstallationandConfiguration
Spark	0.7.3	http://spark.incubator.apache.org/
Impala	1.1.1	http://www.cloudera.com/content/cloudera-content/ cloudera-docs/Impala/latest/Installing-and-Using-Impala/ciiu_install.html
MPICH	1.5	http://www.mpich.org/downloads/

4 Data Generation

In Big Data Bench, We have three kinds of data generation tools to generate text data, graph data and table data. Generally, the process contains two sub steps. The first step is to prepare for generate big data by analyzing the characteristics of the seed data which is real owned by users, and the second sub step is to expand the seed data to big data maintaining the features of seed data.

4.1 Text Data

We provide a data generation tool which can generate data with user specified data scale. It has two steps, firstly, it analyze the seed data which is the user-owned small-scale data; secondly, it generate the big data based on the output of the first step.

Usage

1. **Download the programs**

   tar xzf BigDataBench_Text_datagen.tar.gz
2. **Compile the LDA program**

   make
3. **Train the model**

   Before training data, please convert the file containing seed data to source.txt with this format: put each file's content into each line in source.txt. Then source.txt contains content of all files.

   Basic command-line usage:

   sh train.sh <sourc.txt> <model_name>

   <source.txt>: the file contains all content of seed data

   <model_name>: the name of generated model

   After training the model, a directory is created.
4. **Generate the data**

   Basic command-line usage:

   sh gen_data.sh model_name number_of_files lines_per_file

   <model_name>: the name of model used to generate new data

   < number_of_files >: the number of files to generate

   < lines_per_file >: number of lines in each file

   For example:

   sh gen_data.sh wiki1w_lcj_50 100 1000

   This command will generate 100 files each contains 1000 lines by using model wiki1w.

Note: The tool in current version generates data very slowly, we are trying to improve it. A better version will be released soon.

4.2 Graph Data

Here we use Kronecker to generate data that is both mathematically tractable and have all the structural properties from the real data set. (http://snap.stanford.edu/snap/index.html)
There are **TWO** steps for Kronecker to enlarge real data:
First, use KRONFIT, a fast and scalable algorithm for fitting the Kronecker graph generation model to large real data.
Second, input KRONGEN the parameters you get in the first step to generate data.

Usage

1. **Download the programs**
2. **Train the model**

   Basic command-line usage:

   ./konfit \
   -i:Input graph file (single directed edge per line) (default:'../as20graph.txt')
   -o:Output file prefix (default:'')
   -n0:Innitiator matrix size (default:2)
   -m:Init Gradient Descent Matrix (R=random) (default:'0.9 0.7; 0.5 0.2')
   -p:Initial node permutation: d:Degree, r:Random, o:Order (default:'d')
   -gi:Gradient descent iterations (default:50)
   -l:Learning rate (default:1e-05)
   -mns:Minimum gradient step (default:0.005)
   -mxs:Maximum gradient step (default:0.05)
   -w:Samples to warm up (default:10000)
   -s:Samples per gradient estimation (default:100000)
   -sim:Scale the initiator to match the number of edges (default:'T')
   -nsp:Probability of using NodeSwap (vs. EdgeSwap) MCMC proposal distribution (default:1)

3. **Generate the data**

   Basic command-line usage:

   ./krongen \
   -o:Output graph file name (default:'graph.txt')
   -m:Matrix (in Maltab notation) (default:'0.9 0.5; 0.5 0.1')
   -i:Iterations of Kronecker product (default:5)
   -s:Random seed (0 - time seed) (default:0)

   For example:

   ./kronfit -i:../data-graphMedel/Amazon0505.txt -n0:2 -m:"0.9 0.6; 0.6 0.1" -gi:100 > ../data-outfile/amazon_parameter.txt
   ./krongen -o:../data-outfile/amazon_gen.txt -m:"0.7196 0.6313; 0.4833 0.3601" -i:23

4.3 Table Data

We use Parallel Data Generation Framework to generate table data. The Parallel Data Generation Framework (PDGF) is a generic data generator for database benchmarking. PDGF was designed to take advantage of today's multi-core processors and large clusters of computers to generate large amounts of synthetic benchmark data very fast. PDGF uses a fully computational approach and is a pure Java implementation which makes it very portable.
You can use your own configuration file to generate table data.

Usage

1. **Download the program**
2. **Prepare the configuration files**

The configuration files are written in XML and are by default stored in the *config* folder. PDGF-V2 is configured with 2 XML files: the schema configuration and the generation configuration. The schema configuration (demo-schema.xml) defines the structure of the data and the generation rules, while the generation configuration (demo-generation.xml) defines the output and the post-processing of the generated data.
For the demo, we will generate the files demo-schema.xml and demo-generation.xml which are also contained in the provided .gz file. Initially, we will generate two tables: OS_ORDER and OS_ORDER_ITEM.

- demo-schema.xml
- demo-generation.xml

3. **Generate data**

After creating both demo-schema.xml and demo-generation.xml a first data generation run can be performed. Therefore it is necessary to open a shell, change into the PDGFEnvironment directory.

Basic command-line usage:

```
java -XX:NewRatio=1 -jar pdgf.jar -l demo-schema.xml -l demo-generation.xml -c –s
```

5 Workloads

After generating the big data, we integrate a series of workloads to process the data in our big data benchmarks. In this part, we will introduction how to run the Big Data Benchmark for each workload. It mainly has two steps. The first step is to generate the big data and the second step is to run the applications using the data we generated.

After unpacking the package, users will see six main folders General, Basic Operations, Database Basic Operations, Data Warehouse Basic Operations, Search Engine, Social Network and

Ecommerce System.

5.1 General Basic Operations

Download the file: BigDataBench_BasicOperations.tar.gz

5.1.1 Sort & Wordcount & Grep

Note: Please refer to BigDataBenchV1 for the above three workloads in MapReduce environment. The MPI and Spark versions will be published soon.

5.1.2 BFS (Breath first search)

To prepare

1. Please decompress the file: BigDataBench_BasicOperations.tar.gz

   tar xzf BigDataBench_BasicOperations.tar.gz

2. Decompress the file: graph500.tar.gz

   cd BigDataBench_BasicOperations

   tar xzf graph500.tar.gz

Basic Command-line Usage:

mpirun -np PROCESS_NUM graph500/mpi/graph500_mpi_simple VERTEX_SIZE

Parameters:

PROCESS_NUM: number of process;

VERTEX_SIZE: number of vertex, the total number of vertex is 2^ VERTEX_SIZE

For example: Set the number of total running process of to be 4, the vertex number to be 2^20, the command is:

mpirun -np 4 graph500/mpi/graph500_mpi_simple 20

5.2 Database Basic Operations

We use YCSB to run database basic operations. And, we provide three ways: HBase, Cassandra and MongoDB to run operations for each operation.

To Prepare

Obtain YCSB:

wget https://github.com/downloads/brianfrankcooper/YCSB/ycsb-0.1.4.tar.gz

tar zxvf ycsb-0.1.4.tar.gz

cd ycsb-0.1.4

Or clone the git repository and build:

```
git clone git://github.com/brianfrankcooper/YCSB.git
cd YCSB
mvn clean package
```

We name $YCSB as the path of YCSB for the following steps.

5.2.1 Write

1. For HBase

Basic command-line usage:

```
cd $YCSB
sh bin/ycsb load hbase -P workloads/workloadc -p threads=<thread-numbers> -p
columnfamily=<family> -p recordcount=<recordcount-value> -p hosts=<hostip> -s>load.dat
```

A few notes about this command:

- <thread-number> : the number of client threads, this is often done to increase the amount of load offered against the database.
- <family> : In Hbase case, we used it to set database column. You should have database usertable with column family before running this command. Then all data will be loaded into database usertable with column family.
- <recorcount-value>: the total records for this benchmark. For example, when you want to load 10GB data you shout set it to 10000000.
- <hostip> : the IP of the hbase's master node.

2. For Cassandra

Before you run the benchmark, you should create the keyspace and column family in the Cassandra. You can use the following commands to create it:

```
CREATE KEYSPACE usertable
  with placement_strategy = 'org.apache.cassandra.locator.SimpleStrategy'
and strategy_options = {replication_factor:2};
use usertable;
create column family data with comparator=UTF8Type and
default_validation_class=UTF8Type and key_validation_class=UTF8Type;
```

Basic command-line usage:

```
cd $YCSB
sh bin/ycsb load cassandra-10  -P  workloads/workloadc  -p threads=<thread-numbers>
-p recordcount=<recorcount-value> -p  hosts=<hostips>  -s >load.dat
```

A few notes about this command:

- <thread-number> : the number of client threads, this is often done to increase the amount of load offered against the database.
- <recorcount-value> : the total records for this benchmark. For example, when you want to load 10GB data you shout set it to 10000000.
- <hostips> : the IP of cassandra's nodes. If you have more than one node you should divide with ",".

3. For MongoDB

Basic command-line usage:

cd $YCSB

/bin/ycsb load mongodb -P workloads/workloadc -p threads=<thread-numbers> -p recordcount=<recorcount-value> -p mongodb.url=<mongodb.url> -p mongodb.database=<database> -p mongodb.writeConcern=normal -s >load.dat

A few notes about this command:

- <thread-number> : the number of client threads, this is often done to increase the amount of load offered against the database.
- <recorcount-value>: the total records for this benchmark. For example, when you want to load 10GB data you shout set it to 10000000.
- <mongodb.url>: this parameter should point to the mongos of the mongodb. For example "mongodb://172.16.48.206:30000".
- <database>: In Mongodb case, we used it to set database column. You should have database ycsb with collection usertable before running this command. Then all data will be loaded into database ycsb with collection usertable. To create the database and the collection, you can use the following commands:

  db.runCommand({enablesharding:"ycsb"});

  db.runCommand({shardcollection:"ycsb.usertable",key:{ _id:1}});

5.2.2 Read

1. For HBase

Basic command-line usage:

cd $YCSB

sh bin/ycsb run hbase -P workloads/workloadc -p threads=<thread-numbers> -p columnfamily=<family> -p operationcount=<operationcount-value> -p hosts=<hostip> -s>tran.dat

A few notes about this command:

- <thread-number> : the number of client threads, this is often done to increase the amount of load offered against the database.
- <family> : In Hbase case, we used it to set database column. You should have database usertable with column family before running this command. Then all data will be loaded into database usertable with column family.
- < operationcount-value >: the total operations for this benchmark. For example, when you want to load 10GB data you shout set it to 10000000.
- <hostip> : the IP of the hbase's master node.

2. For Cassandra

Basic command-line usage:

cd $YCSB

sh bin/ycsb run cassandra-10 -P workloads/workloadc -p threads=<thread-numbers> -p operationcount=<operationcount-value> -p hosts=<hostips> -s>tran.dat

A few notes about this command:

- <thread-number> : the number of client threads, this is often done to increase the amount of load offered against the database.
- <operationcount-value> : the total records for this benchmark. For example, when you want to load 10GB data you shout set it to 10000000.
- <hostips> : the IP of cassandra's nodes. If you have more than one node you should divide with ",".

3. For MongoDB

Basic command-line usage:

cd $YCSB

sh bin/ycsb run mongodb -P workloads/workloadc -p threads=<thread-numbers> -p operationcount=<operationcount-value> -p mongodb.url=<mongodb.url> -p mongodb.database=<database> -p mongodb.writeConcern=normal -p mongodb.maxconnections=<maxconnections> -s>tran.dat

A few notes about this command:

- <thread-number> : the number of client threads, this is often done to increase the amount of load offered against the database.
- <operationcount-value> : the total records for this benchmark. For example, when you want to load 10GB data you shout set it to 10000000.
- <mongodb.url>: this parameter should point to the mongos of the mongodb. For example "mongodb://172.16.48.206:30000".
- <database>: In Mongodb case, we used it to set database column. You should have database ycsb with collection usertable before running this command. Then all data will be loaded into database ycsb with collection usertable. To create the database and the collection, you can use the following commands:

  db.runCommand({enablesharding:"ycsb"});

  db.runCommand({shardcollection:"ycsb.usertable",key:{ _id:1}});
- <maxconnections> : the number of the max connections of mongodb.

5.2.3 Scan

1. For HBase

Basic command-line usage:

cd $YCSB

sh bin/ycsb run hbase -P workloads/workloade -p threads=<thread-numbers> -p columnfamily=<family> -p operationcount=<operationcount-value> -p hosts=<Hostip> -p columnfamily=<family> -s>tran.dat

A few notes about this command:

- <thread-number> : the number of client threads, this is often done to increase the amount of load offered against the database.
- <family> : In Hbase case, we used it to set database column. You should have database

usertable with column family before running this command. Then all data will be loaded into database usertable with column family.

- < operationcount-value >: the total operations for this benchmark. For example, when you want to load 10GB data you shout set it to 10000000.
- <hostip> : the IP of the hbase's master node.

2. For Cassandra

Basic command-line usage:

```
cd $YCSB
sh bin/ycsb run cassandra-10 -P  workloads/workloade -p threads=<thread-numbers> -p
operationcount=<operationcount-value> -p hosts=<hostips>  -s>tran.dat
```

A few notes about this command:

- <thread-number> : the number of client threads, this is often done to increase the amount of load offered against the database.
- <operationcount-value> : the total records for this benchmark. For example, when you want to load 10GB data you shout set it to 10000000.
- <hostips> : the IP of cassandra's nodes. If you have more than one node you should divide with ",".

3. For MongoDB

Basic command-line usage:

```
cd $YCSB
sh bin/ycsb run  mongodb  -P workloads/workloade -p threads=<thread-numbers> -p
operationcount=<operationcount-value>  -p mongodb.url=<mongodb.url> -p
mongodb.database=<database> -p mongodb.writeConcern=normal -p
mongodb.maxconnections=<maxconnections>  -s>tran.dat
```

A few notes about this command:

- <thread-number> : the number of client threads, this is often done to increase the amount of load offered against the database.
- <operationcount-value> : the total records for this benchmark. For example, when you want to load 10GB data you shout set it to 10000000.
- <mongodb.url>: this parameter should point to the mongos of the mongodb. For example "mongodb://172.16.48.206:30000".
- <database>: In Mongodb case, we used it to set database column. You should have database ycsb with collection usertable before running this command. Then all data will be loaded into database ycsb with collection usertable. To create the database and the collection, you can use the following commands:

  ```
  db.runCommand({enablesharding:"ycsb"});
  db.runCommand({shardcollection:"ycsb.usertable",key:{ _id:1}});
  ```
- <maxconnections> : the number of the max connections of mongodb.

5.3 Data Warehouse Basic Operations

To Prepare

Hive and Impala(including impala server and impala shell) should be installed. (Please refer to <<Prerequisite>>)

1. We use the PDGF-V2 to generate data. Please refer to section 4.3<<Table Data>>
2. Before importing data, please make sure the 'hive' and 'impala-shell' command are available in your shell environment. You can import data to Hive in this manner:

    sh prepare.sh PATH_OF_ORDER_TABLE PATH_OF_ITEM_TABLE

    Parameters:
    PATH_OF_ORDER_TABLE: path of the order table;
    PATH_OF_ITEM_TABLE: path of the item table.

5.3.1 Select

Basic command-line usage:

1. **For Hive**
   sh run_hive.sh hive select
2. **For Impala**
   sh run.sh impala select

5.3.2 Aggregation

Basic command-line usage:
sh run.sh hive/impala aggregation

5.3.3 Join

Basic command-line usage:
sh run.sh hive/impala join

5.4 Search Engine

Search engine is a typical application in big data scenario. Google, Yahoo, and Baidu accept huge amount of requests and offer the related search results every day. A typical search engine crawls data from the web and indexes the crawled data to provide the searching service.

5.4.1 Search Engine Web Serving

5.4.2 SVM

Note: Please refer to BigDataBench v1 for more information about these two workloads.

5.4.3 PageRank

The PageRank program now we use is obtained from Hibench.

To prepare:

1. Download the file BigDataBench_Search_v2.tar.gz and decompress.
2. Decompress the file BigDataBench_Search_v2/PageRank.tar.gz

Basic command-line usage:

cd PageRank
Perpare: sh prepare.sh
Runnning: sh run.sh

5.4.4 Index

The Index program now we use is obtained from Hibench.

To prepare:

1. Download the file BigDataBench_Search_v2.tar.gz and decompress.
2. Decompress the file BigDataBench_Search_v2/index.tar.gz

Basic command-line usage:

cd index
Perpare: sh prepare.sh
Runnning: sh run.sh

5.5 Social Network

Social networking service has becoming a new typical big data application. A typical social networking service generally contains a convenient a web serving module for users to view and publish information. Besides, it has an efficient graph computation module to generate graph data (for friend recommendation etc.) for each user.

5.5.1 Web Serving

We use the Web Serving workload of CloudSuite to construct the Web Serving of Social Network

System.

Please refer to http://parsa.epfl.ch/cloudsuite/web.html for setup.

5.5.2 Kmeans

The Kmeans program we used is obtained from Mahout.

To Prepare

1. Download the file BigDataBench_SNS.tar.gz and decompress.
2. Decompress the file BigDataBench_SNS/kmeans.tar.gz

Basic command-line usage:

cd kmeans
Perpare: ./prepare-kmeans.sh
Runnning: ./run-kmeans.sh

5.5.3 Connected Components

The Connected Components program we used is obtained from PEGASUS.

To Prepare

1. Copy the graph edge file to the HDFS directory cc_edge
2. Execute ./run_ccmpt.sh

Basic command-line usage:

./run_ccmpt.sh [#_of_nodes] [#_of_reducers] [HDFS edge_file_path]
[#_of_nodes] : number of nodes in the graph
[#_of_reducers] : number of reducers to use in hadoop. - The number of reducers to use depends on the setting of the hadoop cluster. - The rule of thumb is to use (number_of_machine * 2) as the number of reducers.
[HDFS edge_file_path] : HDFS directory where edge file is located
ex: ./run_ccmpt.sh 16 3 cc_edge

5.6 Ecommerce System

A typical ecommerce system provides a friendly web serving, reliable database system and rapid data analysis module. The database system stores information of items, users and biddings. Data analysis is an important module of ecommerce system to analyze users' feature and then promote the bidding amounts by giving the proper recommendation.

With the development of related technologies, E-commerce has already become one of the most important applications on internet. Our big data benchmarking work used various state-of-art algorithms or techniques to access, analyze, store big data and offer E-commerce as follows.

5.6.1 Ecommerce System Web Serving

We use open source tool RUBiS as our Web service and data management workloads Application. Since ten years ago, when E-commerce just became unfolding, it has attracted lot of researchers researching its workload characteristics. RUBiS is an auction site prototype modeled after Ebay that is used to evaluate application design patterns and application servers' performance scalability. The site implements the core functionality of an auction site: selling, browsing and bidding. To run a RUBiS system, please reference to the RUBiS website: http://rubis.ow2.org/index.html.
The download URL is http://forge.ow2.org/project/showfiles.php?group_id=44
You can change the parameters of the payload generator (RUBiS/Client/rubis.properties) for what you need.

Basic command-line usage:

```
vim $RUBiS_HOME/Client/rubis.properties
make emulator
```

5.6.2 Collaborative Filtering Recommendation

Collaborative filtering recommendation is one of the most widely used algorithms in E-com analysis. It aims to solve the prediction problem where the task is to estimate the preference of a user towards an item which he/she has not yet seen.

We use the RecommenderJob in Mahout(http://mahout.apache.org/) as our Recommendation workload, which is a completely distributed itembased recommender. It expects ID1, ID2, value (optional) as inputs, and outputs ID1s with associated recommended ID2s and their scores. As you know, the data set is a kind of graph data.

Before you run the RecommenderJob, you must have HADOOP and MAHOUT prepared. You can use Kronecker (see 4.2.1) to generate graph data for RecommenderJob.

Basic command-line usage:

```
sh prepare-E-com-recommendator.sh
sh run-E-com-recommendator.sh
```

Input parameters according to the instructions:

1. The DIR of your working derictor;
2. The DIR of MAHOUT_HOME.

5.6.3 Bayes

Naive Bayes is an algorithm that can be used to classify objects into usually binary categories. It is one of the most common learning algorithms in Classification. Despite its simplicity and rather naive assumptions it has proven to work surprisingly well in practice.

We use the naivebayes in Mahout(http://mahout.apache.org/) as our Bayes workload, which is a completely distributed classifier.

Basic command-line usage:

sh prepare-E-com-naivebayes.sh

sh run-E-com-naivebayes.sh

Input parameters according to the instructions:

1. The DIR of your working derictor;
2. The DIR of MAHOUT_HOME.

6 Reference

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