BigDataBench 5.0 User Manual

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1 Introduction

1.1 Context

Architecture, system, data management, and AI or machine learning communities pay greater attention to innovative big data and AI algorithms, architecture, and systems. However, complexity, diversity, frequently changed workloads, and rapid evolution of big data and AI systems raise great challenges, as there is a lack of simple but elegant abstractions that facilitate understanding these most important classes of modern workloads. First, for the sake of conciseness, benchmarking scalability, portability cost, reproducibility, and better interpretation of performance data, we need understand what are the most time-consuming classes of unit of computation among big data and AI workloads. Second, for the sake of fairness, the benchmarks must include diversity of data and workloads. Third, for co-design of software and hardware, the benchmarks should be consistent across different communities; Moreover, we need simple but elegant abstractions that help achieve both efficiency and general-purpose.

We specify the common requirements of Big Data and AI workloads only algorithmically in a paper-and-pencil approach, reasonably divorced from individual implementations. We capture the differences and collaborations among IoT, edge, datacenter and HPC in handling Big Data and AI workloads. We consider each big data and AI workload as a pipeline of one or more classes of units of computation performed on initial or intermediate data inputs, each of which we call a data motif. For the first time, among a wide variety of big data and AI workloads, we identify eight data motifs (PACT' 18 paper)—including Matrix, Sampling, Logic, Transform, Set, Graph, Sort and Statistic computation, each of which captures the common requirements of each class of unit of computation. Other than creating a new benchmark or proxy for every possible workload, we propose using data motif-based benchmarks—the combination of one or more data motifs—to represent diversity of big data and AI workloads.

We release an open-source and scalable big data and AI benchmark suite—BigDataBench 5.0---for IoT, Edge, Datacenter and HPC. The current version BigDataBench 5.0 provides 13 representative real-world data sets and 44 benchmarks. The benchmarks cover seven workload types including AI, online services, offline analytics, graph analytics, data warehouse, NoSQL, and streaming from three important application domains: Internet services (including search engines, social networks, e-commerce), recognition sciences, and medical sciences. Our benchmark suite includes micro benchmarks, each of which is a single data motif, components benchmarks, which consist of the data motif combinations, and end-to-end application benchmarks, which are the combinations of component benchmarks. Meanwhile, data sets have great impacts on workloads behaviors and running performance (our CGO' 18 paper). Hence, data varieties are considered with the whole spectrum of data types including structured, semi-structured, and unstructured data. Currently, the included data sources are text, graph, table, and image data. Using real data sets as the seed, the data generators—BDGS—generate synthetic data by scaling the seed data while keeping the data characteristics of raw data.

Modern datacenter computer systems are widely deployed with mixed workloads to improve system utilization and save cost. However, the throughput of latency-critical workloads is dominated by their worst-case performance-tail latency. To model this important application scenario, we propose an end-to-end application benchmark---DCMix to generate mixed workloads whose latencies range from microseconds to minutes with four mixed execution modes.

Modern Internet services workloads are notoriously complex in terms of industry-scale architecture fueled with machine learning algorithms. As a joint work with Alibaba, we release an end-to-end application benchmark---E-commerce Search to mimic complex modern Internet services workloads.

To measure and rank high performance AI computer systems (HPC AI) or AI supercomputers, we also release an HPC AI benchmark suite (AI500), consisting of micro benchmarks, each of which is a single data motif, and component benchmarks, e.g., resnet 50.

1.2 Environment

This document presents user manual information on BigDataBench 5.0 – including a brief introduction and the setting up guidelines of big data and AI software stacks, and operating guide of all workloads in BigDataBench 5.0. The information and specifications contained are for researchers who are interested in big data and AI benchmarking.

Note that the user manual information in the following passage are tested in the environment as follows.

Recommended browner: IE or Chrome.

Recommended OS : Centos 6.0 or later.

Libraries:

JDK 1.6 or later (Recommend version: jdk1.8.0_65)

C compiler, such as gcc, and C++ compiler, such as g++.

1.3 Format Specification

The following typographic conventions are used in this user manual:

Convention	Description
Bold	Bold for emphasis.
Italic	Italic for fold and file names.
$command	$command for command lines.
Contents	Contents for contents in configuration files.
Courier font	Courier font for screen output.
Footnote	Some exception explanations are put in footnote.

2 Overview of Software Packages and Workloads

Benchmark	Benchmark Type	Workload Type	Dataset	Software stacks
Sort	Micro Benchmark	Offline analytics	Wikipedia entries	Hadoop, Spark, Flink, MPI
Grep		Offline analytics	Wikipedia entries	Hadoop, Spark, Flink, MPI
		Streaming	Random generate	Spark Streaming
WordCount		Offline analytics	Wikipedia entries	Hadoop, Spark, Flink, MPI
MD5		Offline analytics	Wikipedia entries	Hadoop, Spark, MPI
Connected Component		Graph analytics	Facebook social network	Hadoop, Spark, Flink, MPI, GraphLab
RandSample		Offline analytics	Wikipedia entries	Hadoop, Spark, MPI
FFT		Offline analytics	Two-dimensional matrix	Hadoop, Spark, MPI
Matrix Multiply		Offline analytics	Two-dimensional matrix	Hadoop, Spark, MPI
Read		NoSQL	ProfSearch resumes	HBase, MongoDB
Write		NoSQL	ProfSearch resumes	HBase, MongoDB
Scan		NoSQL	ProfSearch resumes	HBase, MongoDB
OrderBy		Data warehouse	E-commerce transaction	Hive, Spark-SQL, Impala
Aggregation		Data warehouse	E-commerce transaction	Hive, Spark-SQL, Impala
Project		Data warehouse	E-commerce transaction	Hive, Spark-SQL, Impala
Filter		Data warehouse	E-commerce transaction	Hive, Spark-SQL, Impala
Select		Data warehouse	E-commerce transaction	Hive, Spark-SQL, Impala
Union		Data warehouse	E-commerce transaction	Hive, Spark-SQL, Impala
Convolution		AI	Cifar, ImageNet	TensorFlow, Pthread, PyTorch
Fully Connected		AI	Cifar, ImageNet	TensorFlow, Pthread, PyTorch
Relu		AI	Cifar, ImageNet	TensorFlow, Pthread, PyTorch
Sigmoid		AI	Cifar, ImageNet	TensorFlow, Pthread, PyTorch
Tanh		AI	Cifar, ImageNet	TensorFlow, Pthread, PyTorch
MaxPooling		AI	Cifar, ImageNet	TensorFlow, Pthread, PyTorch
AvgPooling		AI	Cifar, ImageNet	TensorFlow, Pthread, PyTorch
CosineNorm		AI	Cifar, ImageNet	TensorFlow, Pthread, PyTorch
BatchNorm		AI	Cifar, ImageNet	TensorFlow,

				Pthread, PyTorch
Dropout		AI	Cifar, ImageNet	TensorFlow, Pthread, PyTorch
Image Classification	Component Benchmark	AI	ImageNet	TensorFlow, PyTorch
Image Generation		AI	LSUN	TensorFlow, PyTorch
Text-to-Text Translation		AI	WMT English-German	TensorFlow, PyTorch
Image-to-Text		AI	MS COCO dataset	TensorFlow, PyTorch
Image-to-Image		AI	Cityscapes	TensorFlow, PyTorch
Speech-to-Text		AI	Librispeech	TensorFlow, PyTorch
Face embedding		AI	Labeled faces in the wild	TensorFlow, PyTorch
Object detection		AI	Microsoft COCO	TensorFlow, PyTorch
Collaborative Filtering (CF)		Offline Analytics	MovieLens	Hadoop, Spark
PageRank		Graph Analytics	Google web graph	Hadoop, Spark, Flink, GraphLab, MPI
LDA		Offline Analytics	Wikipedia entries	Hadoop, Spark, MPI
K-means		Offline Analytics	Facebook social network	Hadoop, Spark, Flink, MPI
		Streaming	Random generate	Spark streaming
Navie bayes		Offline Analytics	Amazon movie review	Hadoop, Spark, Flink, MPI
SIFT		Offline Analytics	ImageNet	Hadoop, Spark, MPI
Index		Offline Analytics	Wikipedia entries	Hadoop, Spark
Rolling top words		Streaming	Random generate	Spark streaming, JStorm
DCMix	Application Benchmark	Datacenter	Mixed	Mixed
E-commerce Search		Internet Service	Alibaba	Alibaba framework
HPC AI benchmark	HPC Benchmark	HPC	Scientific data	TensorFlow

3 Installation and Configuration of Software

3.1 Setting up Hadoop

Hadoop software library is a framework that allows for the distributed processing of large data sets across clusters of computers using simple programming models.

1) Prerequisites

Java JDK: version 1.6 or later (Recommend version: jdk1.8.0_65)

Hadoop version: we recommend version 2.7.1, which was used and tested in our environment.

2) Download Hadoop

Download Hadoop 2.7.1 from the following link:

https://archive.apache.org/dist/hadoop/core/hadoop-2.7.1/hadoop-2.7.1.tar.gz

3) Basic Configuration

Step 1. Setup passphraseless ssh

Master node must ssh to slave nodes without a passphrase.

If you use a standalone mode, the master and slave nodes are the same one.

If you cannot ssh to nodes without a passphrase, execute the following commands at slave nodes:

```
$ ssh-keygen -t dsa -f $HOME/.ssh/id_dsa -P ""
```

This command will generate two files---$HOME/.ssh/id_dsa (private key) and $HOME/.ssh/id_dsa.pub (public key).

Copy $HOME/.ssh/id_dsa.pub to Master nodes. On slave nodes run the following commands:

```
$ cat id_dsa.pub >> $HOME/.ssh/authorized_keys
$ chmod 0600 $HOME/.ssh/authorized_keys
```

On the master node test the results by ssh to slave nodes:

```
$ ssh -i $HOME/.ssh/id_dsa server
```

Step 2. Configure Hadoop

Decompress the Hadoop package.

```
$ tar -zxvf hadoop-2.7.1.tar.gz
```

Edit the configuration file:

```
$ cd hadoop-2.7.1/etc/hadoop
```

Add the following contents in “hadoop-env.sh”：

```
export JAVA_HOME=/path/to/java_home
```

Add the following contents in “core-site.xml”：

```
<configuration>
<property>
<name>hadoop.tmp.dir</name>
<value>/path/to/tmp_data</value>
<description>Abase for other temporary directories.</description>
</property>
<property>
```

```
<name>fs.default.name</name>
<value>hdfs://master_node_hostname:9100</value>
</property>
</configuration>
```

Add the following contents in “hdfs-site.xml” :

```
<configuration>
<property>
<name>dfs.name.dir</name>
<value>/path/to/store/metadata</value>
<description> </description>
</property>
<property>
<name>dfs.data.dir</name>
<value>/path/to/store/hdfs_data</value>
<description> </description>
</property>
<property>
<name>dfs.replication</name>
<value>1</value>
</property>
</configuration>
```

Add the following contents in “mapred-site.xml”

```
<configuration>
<property>
<name>mapred.job.tracker</name>
<value>master_node_hostname:9200</value>
</property>
<property>
<name>dfs.blocksize</name>
 <value>blocksizeNumBytes</value>
</property>
</configuration>
```

Add the following contents in “yarn-site.xml”

```
<configuration>
<property>
   <name>yarn.resourcemanager.hostname</name>
   <value>hostname</value>
</property>
<property>
   <name>yarn.nodemanager.aux-services</name>
   <value>mapreduce_shuffle</value>
</property>
```

```
<property>
   <name>yarn.nodemanager.resource.cpu-vcores</name>
   <value>core_number</value>
</property>
<property>
  <name>yarn.scheduler.minimum-allocation-mb</name>
      <value>min_mb</value>
      <description></description>
  </property>
<property>
      <name>yarn.scheduler.maximum-allocation-mb</name>
      <value>max_mb</value>
      <description></description>
  </property>
  <property>
      <name>yarn.nodemanager.resource.memory-mb</name>
      <value>res_md</value>
      <description></description>
  </property>
</configuration>
```

Add slave hostname/IP in “slaves” file

```
hostname1
hostname2
```

Add the Hadoop home path to the environment variable of the system.

```
$ vim ~/.bashrc
```

Add:

```
export HADOOP_HOME=/path/to/hadoop
export PATH=$PATH:$HADOOP_HOME/bin
```

```
$ source /.bashrc
```

Then scp all this package (i.e., hadoop-2.7.1) to all slave nodes and put them under the same directory.

3) Start Hadoop

Step 1. Format the HDFS:

```
$ cd hadoop-2.7.1
$ bin/hadoop namenode -format
```

Step 2. Start Hadoop:

```
$ sbin/start-all.sh
```

4) Stop Hadoop:

```
$ sbin/stop-all.sh
```

3.2 Setting up Spark

1) Prerequisites

Java JDK: version 1.6 or later

Scala: version 2.10.4 or later

Hadoop: version 2.7.1 or other 1.x/2.x version

Spark: recommend version 1.5.2, which are tested in our environment, or other 1.x version

2) Download Spark

Download the prebuild package:

https://archive.apache.org/dist/spark/spark-1.5.2/spark-1.5.2-bin-hadoop2.6.tgz

3) Basic Configuration

Step 1. Setup passphraseless ssh

Master node must ssh to work nodes without a passphrase.

If you use a standalone mode, the master and work nodes are the same one.

If you cannot ssh to nodes without a passphrase, execute the following commands at worker nodes:

```
$ ssh-keygen -t dsa -f $HOME/.ssh/id_dsa -P ""
```

This command will generate two files---$HOME/.ssh/id_dsa (private key) and $HOME/.ssh/id_dsa.pub (public key).

Copy $HOME/.ssh/id_dsa.pub to Master nodes. Run the following commands on worker nodes:

```
$ cat id_dsa.pub » $HOME/.ssh/authorized_keys
$ chmod 600 $HOME/.ssh/authorized_keys
```

On the master node test the results through ssh to worker nodes:

```
$ ssh -i $HOME/.ssh/id_dsa server
```

Step 2. Configure Spark

Decompress the Spark package.

```
$ tar -zxvf spark-1.5.2-bin-hadoop2.6.tgz
```

Edit the configuration file:

```
$ cd spark-1.5.2-bin-hadoop2.6/conf
$ cp spark-env.sh.template spark-env.sh
```

Edit spark-env.sh

```
SPARK_MASTER_IP= MASTER_HOSTNAME
export SCALA_HOME=/usr/lib/scala-2.10.4
export JAVA_HOME=/usr/java/jdk1.8.0_65
export HADOOP_HOME=/path/to/hadoop-2.7.1
export HADOOP_CONF_DIR=/path/to/hadoop-2.7.1/etc/hadoop
export SPARK_EXECUTOR_INSTANCES=instance_num
export SPARK_EXECUTOR_CORES=core_num
export SPARK_EXECUTOR_MEMORY=xxG
export SPARK_DRIVER_MEMORY=xxG
```

```
$ cp spark-defaults.conf.template spark-defaults.conf
```

Edit spark-defaults.conf

```
spark.master                spark:// MASTER_HOSTNAME:7077
spark.eventLog.enabled          true
spark.default.parallelism 100
spark.storage.memoryFraction 0.4
spark.shuffle.memoryFraction 0.6
spark.shuffle.manager hash
spark.shuffle.compress true
spark.broadcast.compress true
spark.shuffle.file.buffer 64k
spark.storage.unrollFraction 0.5
spark.serializer org.apache.spark.serializer.KryoSerializer
spark.rdd.compress true
```

Edit slaves:

```
WORKER_HOSTNAME #each work per line
```

Add the Spark home path to the environment variable of the system.

```
$ vim  ~/.bashrc
```

ADD

```
export SPARK_HOME=/path/to/spark
export PATH=$PATH:$SPARK_HOME/sbin
```

```
$ source  ~/.bashrc
```

3) Start Spark

```
$ cd spark-1.5.2-bin-hadoop2.6/
$ sbin/start-all.sh
```

4) Stop Spark

```
$sbin/stop-all.sh
```

3.3 Setting up MPI

Setting up Software MPICH2

MPICH2 is a portable implementation of the MPI2.2 standard. In this manual, we use the version of mpich2-1.5, for you own installation, you can also choose a higher version.

1) Prerequisites

a C compiler, such as gcc.

a C++ compiler, such as g++

2) Download mpich2

Download links for the latest stable release can always be found on https://www.mpich.org/downloads/

If you want to download the version of mpich2-1.5.tar.gz, you can download at http://www.mpich.org/static/downloads/1.5/

3) Basic Installation

Step 1. Unpack the tar file

```
$ tar -zxvf mpich2-1.5.tar.gz
$ cd mpich2-1.5
```

Step 2. Configure

Choosing an non-existent or empty installation directory, such as /home/mpich2-ins; Command "echo $SHELL" to know the current shell your terminal program used, we use CentOS operating system and bash shell;

For shell of bash and sh, using the following command to configure:

```
$./configure –prefix=/home/mpich2-ins 2>$1 | tee c.txt
```

Step 3. Build

Build command:

```
$ make 2>$1 | tee m.txt
```

Step 4. Install

Install command:

```
$ make install 2>$1 | tee mi.txt
```

Step 5. Add the bin subdirectory to the PATH environment variable

For shell of bash and sh, using the command:

```
$vim ~/.bashrc
```

```
export PATH=$PATH:/home/mpich2-ins/bin
```

Save and exit vim.

```
$ source ~/.bashrc
```

4) Check

Step 1. Checking the path

Using the command to display the path to your bin subdirectory:

```
$which mpicc
$which mpic++
```

In our example, the first command should display "/home/mpich2-ins/bin/mpicc".

Step 2. Checking the location on all machines

The installation directory on all machines should be the same. One method is to install mpich2 on one machine and share its installation directory with other machines, the other method is to install mpich2 on all machines with the same installation directory.

5) Use MPICH2 to run programs

Step 1. Go into the example directory

In the installation package, such as mpich2-1.5.tar.gz, there is an example direc-tory to test.

Step 2. Compile an example C program using mpicc

Using the command to produce corresponding executable file:

```
$ mpicc cpi.c -o cpi
```

This command will produce an executable file named cpi

Step 3. Run the program using multiple processes on one or more machines

Using the command to run the program on local machine:

```
$ mpirun -n 4 ./cpi
```

Note that the number followed -n is the number of processes, here 4 means four processes.

Using the command to run the program on multiple machines;

```
$ vim machine_file #the machine_file contains the information of all machines
```

One example of machine_file, including 3 nodes named node1, node2 and node3:

```
node1
node2
node3
```

Save and exit vim.

```
$ mpirun -f machine_file -n 3 ./cpi
```

Note: -f parameter specificies the machine information, and -n parameter speci-ficies the process number After typing the above mpirun command, the terminal will display the process information and the value of pi, such as

Process 0 of 3 is on node1

Process 1 of 3 is on node2

Process 2 of 3 is on node3

pi is approximately 3.1415926544231239, Error is XXX wall clock time = XXX

3.4 Setting up Hive

Hive facilitates querying and managing large datasets residing in distributed storage. Hive provides a mechanism to project structure onto this data and query the data using a SQL-like language called HiveQL.

1) Prerequisites

Java JDK: version 1.6 or later

Hadoop: we recommend version 2.7.1, which was used and tested in our envi-ronment.

2) Download and Install Hive

Step 1. Download the most recent stable release of Hive

We recommend version 1.2.1 (http://archive.apache.org/dist/hive/hive-1.2.1/), which was used and tested in our environment.

Step 2. Unpack the tarball

```
$ tar -xzvf hive-1.2.1.tar.gz
```

Step 3. Set environment variable

HIVE_HOME(/path/to/hive-1.2.1), add $HIVE_HOME/bin to your PATH.

```
$ vim ~/.bash_profile
```

Edit the ~/.bash_profile:

```
export HIVE_HOME=/path/to/hive-1.2.1
export PATH=$HIVE_HOME/bin:$PATH
```

3) Basic Configuration

Step 1. Copy the configuration file from template.

```
$ cd $HIVE_HOME/conf
$ cp hive-env.sh.template hive-env.sh
$ cp hive-default.xml.template hive-site.xml
```

Step 2. Configure $HIVE_HOME/conf/hive-env.sh.

Edit hive-env.sh:

```
HADOOP_HOME=$HADOOP_HOME
export HIVE_CONF_DIR=$HIVE_HOME/conf
export HIVE_AUX_JARS_PATH=$HIVE_HOME/lib
```

Make hive-env.sh effective:

```
$ source hive-env.sh
```

Step 3. Create the following directory to save the hive relevant data on hdfs:

```
$ HADOOP_HOME/bin/hadoop fs -mkdir /tmp
$ HADOOP_HOME/bin/hadoop fs -mkdir /user/hive/warehouse
$ HADOOP_HOME/bin/hadoop fs -chmod g+w /tmp
$ HADOOP_HOME/bin/hadoop fs -chmod g+w /user/hive/warehouse
```

4) Start Hive

Make sure that you have successfully started Hadoop.

Type the following at the command line to start running hive, and enter Hive CLI.

```
$ HIVE_HOME/bin/hive
```

5) Test Hive

In Hive CLI, Type the following command to test whether Hive have been successfully installed. If return 'OK' , install Hive successfully.

```
$ hive > show tables;
```

6) Stop Hive

In Hive CLI, Type the following command:

```
$ hive > exit;
```

3.5 Setting up hive-0.10.0-cdh4.2.0(for Impala)

1) Prerequisites

CentOS: 6.5

Java JDK: version 1.6 or later

Hadoop: hadoop-2.0.0-cdh4.2.0

Mysql: 5 or later

2) Download and Install hive-0.10.0-cdh4.2.0

Step 1. Download the hive-cdh from cloudera website.

We recommend hive-0.10.0-cdh4.2.0, which was tested in our environment.

http://archive.cloudera.com/cdh4/cdh/4/hive-0.10.0-cdh4.2.0.tar.gz

Step 2. Unpack the tarball.

```
$ tar -xzvf hive-0.10.0-cdh4.2.0.tar.gz
```

Step 3. Set environment variable

HIVE_HOME (/path/to/hive-0.10.0-cdh4.2.0), add HIVE_HOME to your PATH.

```
$ vim ~/.bashrc
```

Edit the ~/.bashrc file and add:

```
export HIVE_HOME=/path/to/hive-0.10.0-cdh4.2.0
export PATH=$HIVE_HOME/bin:$PATH
```

```
$ source ~/.bashrc
```

3) Basic Configuration

Step 1. Enter the directory of configuration file.

```
$ cd $HIVE_HOME/conf
$ cp hive-env.sh.template hive-env.sh
$ cp hive-default.xml.template hive-site.xml
```

Step 2. Configure $HIVE_HOME/conf/hive-env.sh.

Edit hive-env.sh and add:

```
HADOOP_HOME=$HADOOP_HOME
export HIVE_CONF_DIR=$HIVE_HOME/conf
export HIVE_AUX_JARS_PATH=$HIVE_HOME/lib
```

```
$ source hive-env.sh
```

Step 3. Download mysql-connector-java.jar, and transfer mysql-connector-java.jar to $HIVE_HOME/lib.

```
$ wget http://mirrors.sohu.com/mysql/Connector-J/mysql-connector -java-5.1.35.tar.gz
$ tar xzf mysql-connector-java-5.1.35.tar.gz
$ cp mysql-connector-java-5.1.35-bin.jar $HIVE_HOME/lib
```

Step 4. After Starting Mysql, establish appropriate MySQL account for Hive, and give suffi cient authority.

```
$mysql -uroot -phadoophive
mysql>CREATE DATABASE metastore;
mysql>USE metastore;
mysql>SOURCE /usr/lib/hive/scripts/metastore/upgrade/mysql/hive -schema-0.10.0.mysql.sql;
mysql> CREATE USER 'hive'@'%' IDENTIFIED BY 'hadoophive';
mysql>CREATE USER 'hive'@'localhost' IDENTIFIED BY 'hadoophive';
mysql>REVOKE ALL PRIVILEGES, GRANT OPTION FROM 'hive'@'%';
mysql>REVOKE ALL PRIVILEGES, GRANT OPTION FROM 'hive'@'localhost';
mysql>GRANT SELECT,INSERT,UPDATE,DELETE,LOCK TABLES,EXECUTE ON metastore.* TO 'hive'@'%';
mysql>GRANT SELECT,INSERT,UPDATE,DELETE,LOCK TABLES,EXECUTE ON metastore.* TO 'hive'@'localhost'; mysql>FLUSH PRIVILEGES;
mysql> quit;
```

Step 5. Configure Hive_HOME/hive-site.xml to Integrate Mysql as the metadata of Hive.

```
$ sudo vim $HIVE_HOME/conf/hive-site.xml
```

Edit core-site.xml:

```
<!–?xml version="1.0"?–>
<!–?xml-stylesheet type="text/xsl" href="configuration.xsl"?–>
<configuration>
<property>
<name>javax.jdo.option.ConnectionURL</name>
<value>jdbc:mysql://localhost:3306/metastore?createDatabaseIfNotExist=true</value> <description>the URL of the MySQL database</description>
</property>
```

```
<property>
<name>javax.jdo.option.ConnectionDriverName</name>
<value>com.mysql.jdbc.Driver</value>
</property>
<property>
<name>javax.jdo.option.ConnectionUserName</name>
<value>hive</value>
</property>
<property>
<name>javax.jdo.option.ConnectionPassword</name>
<value>hadoophive</value>
</property>
</configuration>
```

```
$ sudo service hive-metastore start
$ sudo service hive-server start
$ sudo -u hive hive
```

4) Start Hive-metastore and Hive-server

```
$ HIVE_HOME/bin/hive
```

5) Test Hive

In Hive CLI, Type the following command to test whether Hive have been successfully installed. If return ’ OK’ , install Hive successfully.

```
$ hive > show tables;
```

6) Stop Hive

In Hive CLI, Type the following command:

```
$ hive > exit;
```

3.6 Setting up Impala

1) Prerequisites

CentOS: 6.5

Java JDK: version 1.6 or later

Hadoop: hadoop-2.0.0-cdh4.2.0

Hive: hive-0.10.0-cdh4.2.0

MySQL:5 or later

Note: the version of cdh, hive and impala need to match; impala requires specific linux version. The details can be found in official document, which are shown: http://www.cloudera.com/content/cloudera-content/cloudera-docs/Impala/latest/PDF/Installing-and-Using-Impala.pdf.

2) Download and install Impala

Step 1. Download the all rpm package from website

http://archive.cloudera.com/ impala/redhat/6/x86_64/impala/1/RPMS/x86_64

Here, we use impala-1.0.1 in our environment. There rpm packages include:

impala-1.0-1.p0.819.el6.x86_64.rpm,

impala-debuginfo-1.0-1.p0.819.el6.x86_64.rpm,

impala-server-1.0-1.p0.819.el6.x86_64.rpm,

impala-shell-1.0-1.p0.819.el6.x86_64.rpm,

impala-state-store-1.0-1.p0.819.el6.x86_64.rpm

Step 2. Download bigtop-utils-0.4+300-1.cdh4.0.1.p0.1.el6.noarch.rpm

http://
archive.cloudera.com/impala/redhat/6/x86_64/impala/1/RPMS/noarch/

Step 3. Download libevent-1.4.13-4.el6.x86_64.rpm

http://rpm.pbone.net/index.php3?stat=26&dist=79&size=67428&name=libevent-1.4.13-4.el6.x86_64. rpm

Step 4. Install rpm packages in datanode and hive node.

```
$rpm -ivh bigtop-utils-0.4+300-1.cdh4.0.1.p0.1.el6.noarch.rpm $rpm -ivh libevent-1.4.13-4.el6.x86_64.rpm
$rpm -ivh impala-1.0-1.p0.819.el6.x86_64.rpm
$rpm -ivh impala-server-1.0-1.p0.819.el6.x86_64.rpm
$rpm -ivh impala-server-1.0-1.p0.819.el6.x86_64.rpm
$rpm -ivh impala-shell-1.0-1.p0.819.el6.x86_64.rpm
$rpm -ivh impala-debuginfo-1.0-1.p0.819.el6.x86_64.rpm
```

3) Basic Configuration

Step 1. Copy configuration files

Copy hive-site.xml, core-site.xml and hdfs-site.xml to the default directory of configuration directory /etc/impala/conf.

```
$ cp $HIVE_HOME/conf/hive-site.xml /etc/impala/conf/hive-site.sh
$cp $HADOOP_HOME/etc/hadoop/core-site.xml /etc/impala/conf/ core-site.xml
$cp $HADOOP_HOME/etc/hadoop/hdfs-site.xml /etc/impala/conf/ hdfs-site.xml
```

Step 2. In the datanode, configure /etc/impala/conf/hive-site.xml.

```
$cd /etc/impala/conf
```

In hive-site.xml, modify the mysql address:

```
<property>
<name>javax.jdo.option.ConnectionURL</name>
<value>jdbc:mysql://localhost:3306/hive?createDatabaseIfNotExist=true</value> <description>JDBC connect string for a JDBC metastore</description> </property>
```

Step 3. In all impala nodes, configure /etc/impala/conf/core-site.xml.

Edit core-site.xml:

```
<property>
<name>dfs.client.read.shortcircuit</name>
<value>true</value>
</property>
<property>
<name>dfs.client.read.shortcircuit.skip.checksum</name>
<value>false</value>
</property>
<property>
<name>fs.defaultFS</name>
<value>hdfs://172.18.11.206:12900</value>
</property>
```

Note: 172.18.11.206 is the ip address of the test impala node.

Step 4. In all impala node, configure /etc/impala/conf/hdfs-site.xml.

Edit hdfs-site.xml,

```
<property>
<name>dfs.client.read.shortcircuit</name>
<value>true</value>
</property>
<property>
<name>dfs.domain.socket.path</name>
<value>/var/run/hadoop-hdfs/dn._PORT</value>
</property>
<property>
<name>dfs.datanode.hdfs-blocks-metadata.enabled</name>
<value>true</value>
</property>
<property>
<name>dfs.client.file-block-storage-locations.timeout</name>Âă
<value>10000</value>
</property>
```

Step 5. In all impala node, modify /etc/default/impala.

```
IMPALA_STATE_STORE_HOST=172.18.11.206
IMPALA_STATE_STORE_PORT=24000
IMPALA_BACKEND_PORT=22000
IMPALA_LOG_DIR=/var/log/impala
IMPALA_STATE_STORE_ARGS= “-log_dir=${IMPALA_LOG_DIR}
state_store_port=${IMPALA IMPALA_SERVER_ARGS= “n
-log_dir=$IMPALA_LOG_DIR n
-state_store_port=$IMPALA_STATE_STORE_PORT n
-use_statestore n
-state_store_host=$IMPALA_STATE_STORE_HOSTn
```

```
-be_port=$IMPALA_BACKEND_PORT"
ENABLE_CORE_DUMPS=false
LIBHDFS_OPTS=-Djava.library.path=/usr/lib/impala/lib
MYSQL_CONNECTOR_JAR=$HIVE_HOME/lib/mysql-connector-java-5.1.35.jar
IMPALA_BIN=/usr/lib/impala/sbin
IMPALA_HOME=/usr/lib/impala
HIVE_HOME=$HIVE_HOME
#HBASE_HOME=/usr/lib/hbase
IMPALA_CONF_DIR=/etc/impala/conf
HADOOP_CONF_DIR=$HADOOP_HOME/etc/hadoop
HIVE_CONF_DIR=$HIVE_HOME/conf
#HBASE_CONF_DIR=/etc/impala/conf
```

4) Start Impala

```
$ sudo service impala-state-store restart
$ sudo service impala-server restart
```

5) Test Impala

Use the follow command to view the start status of impala.

```
$ps -ef |grep impala
```

Enter the impala shell chient.

```
$ impala-shell
```

The Impala shell information will be printed on the screen:

Welcome to the Impala shell. Press TAB twice to see a list of available comma Copyright (c) 2012 Cloudera, Inc. All rights reserved. (Shell build version: Impala Shell v1.0.1 (df844fb) built on Tue Jun 4 08:0813) [Not connected] >

In Impala CLI, input the follow command to connect the impala node.

[Not connected] > connect 172.18.11.206

The connect information will be printed on the screen:

Connected to 172.18.11.206:21000 Server version: impalad version 1.0.1 RELEASE (build df844fb967cec8740f08d3527ef)

6) Stop Impala

In Impala CLI, Type the following command:

```
[172.18.11.206:21000] > exit;
```

3.7 Setting up MySQL

MySQL is an open source relational database management system (RDBMS).

1) Prerequisites

CentOS: 6.5

2) Install MySQL

Step 1: Install Mysql by YUM

```
$ sudo yum install mysql-server
```

Step 2: Initialize Mysql service

The information of initialization will be printed on the screen:

```
$ sudo /usr/bin/mysql_secure_installation
```

[...]
Enter current password for root (enter for none): press âĂ ŸenterâĂ Ź key
OK, successfully used password, moving on... [...]
Set root password? [Y/n] Y
New password:hadoophive
Re-enter new password:hadoophive
Remove anonymous users? [Y/n] Y
[...]
Disallow root login remotely? [Y/n] N
[...]
Remove test database and access to it [Y/n] Y [...]
Reload privilege tables now? [Y/n] Y
All done!

3) Test Mysql service

Step 1. Enter Mysql CLI.

```
$ mysql -uroot -phadoophive
```

Step 2. In Mysql CLI, Type the following command to test whether Hive have been successfully installed. If return ' OK' , install Hive successfully.

```
$ mysql>show table;
```

3.8 Setting up TensorFlow

1) Prerequisites

python, pip, numpy, scipy

2) Download and install TensorFlow

We recommend TensorFlow 1.1.0 version.

```
$ pip install --upgrade
https://storage.googleapis.com/tensorflow/linux/cpu/tensorflow-1.1.0-cp27-none-linux_x86_64.whl
```

3) Test TensorFlow

```
$ python
>>>import tensorflow
>>>
```

If command "import tensorflow" doesn't return errors, then TensorFlow is successfully installed.

3.9 Setting up PyTorch

We recommend PyTorch 1.0.1

1) Prerequisites

python, pip, numpy, scipy

2) Download and install PyTorch

pip install with Python 2.x version:

```
pip3 install torch torchvision
```

pip install with Python 3.x version:

```
pip install torch torchvision
```

conda install:

```
conda install pytorch torchvision -c pytorch
```

conda install with specific cuda version:

```
conda install pytorch torchvision cudatoolkit=10.0 -c pytorch
```

install from source:

Follow instructions at this URL: https://github.com/pytorch/pytorch#from-source

3) Test PyTorch

```
$ python
>>>import torch
>>>
```

If command "import torch" doesn't return errors, then PyTorch is successfully installed.

4 Workloads

4.1 BDGS

BigDataBench is accompanied by a Big Data generation tools, called BDGS (Big Data Generator Suite). It is a comprehensive suite developed to generate synthetic big data while preserving their 4V properties. It can generate Text, Graph and Table data.

Specifically, our BDGS can generate data using a sequence of three steps.

- First, BDGS selects application-specific and representative real-world data sets.
- Second, it constructs data generation models and derives their parameters and con-figurations from the data sets.
- Finally, given a big data system to be tested, BDGS generates synthetic data sets that can be used as inputs of application specific workloads.

In the release edition, BDGS consist of three parts: Text generator, Graph generator, and Table generator.

4.1.1 Get BDGS

The BDGS has been packaged in each the benchmark suite, users do not need to download separately. User can download it from the following link:

http://prof.ict.ac.cn/bdb_uploads/bdb_4/BigDataGeneratorSuite.tar.gz

Also, users can execute the obtain BDGS in each benchmark directory. Such as in http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_Hadoop.tar.gz

4.1.2 Compile BDGS

The BDGS is pre-compiled, and if it is not compatible with users' system, users can compile it by the following ways:

1) Pre-required software

The BDGS depends gls, if the systems do not have the package installed.

```
$ wget http://prof.ict.ac.cn/bdb_uploads/bdb_4/BigDataGeneratorSuite.tar.gz
$ cd BigDataGeneratorSuite
```

2) Compile Text data generate

Cd to the directory, install gsl and execute make command:

```
$ cd BigDataGeneratorSuite/Text_datagen
$ tar -xf gsl-1.15.tar.gz
$ cd gsl-1.15 & ./configure & make & make install
$ cd ..
$ make
```

3) Compile Graph data generate:

Cd to the directory and execute make command:

```
$ cd BigDataGeneratorSuite/Graph_datagen
$ make
```

If there are some error about the incompatible of Snap when executes make command, users need to recompile the snap-core and update the Snap.O:

```
$ cd snap-core
$ make
$ mv Snap.o ../
```

And the execute the make command under directory of BigDataGeneratorSuite/Graph_datagen again:

```
$ cd ../
$ make
```

4) Compile Table data generate:

Cd to the directory and execute make command:

```
$ cd BigDataGeneratorSuite/Table_datagen/personal_generator
$ make
```

4.1.3 Generate data

How to generate data will be explained in "Prepare the input" section of each workload running instruction.

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 introduce how to run the Benchmark for each workload. It typically consists of two steps. The first step is to generate or prepare the data and the second step is to run the applications.

4.2 Micro Benchmarks

Data motifs are fundamental concepts and units of computation among a majority of big data and AI workloads. We design a suite of micro benchmarks, each of which is a single data motif implementation.

4.2.1 Sort, Grep, WordCount, MD5

The instructions of Sort, Grep, WordCount and MD5 workloads are similar, so we put them together. Here we use sort as an example, Grep, WordCount and MD5 running processes are the same, you can just change the "Sort" to "Grep" or "WordCount" or "MD5" in the following commands.

1) Hadoop based

Required Software Stacks Hadoop and BGDS

Step 1. Get workloads from BigDataBench

Download the benchmark package from

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz

Step 2. Decompress the Hadoop package.

```
$ tar -zxvf BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz
```

Install gsl：

```
$ cd BigDataBench_V5.0_BigData_MicroBenchmark/
$ ./prepar.sh
```

Step 3. Prepare the input

```
$ cd Hadoop/Sort
$./genData-sort.sh <size>
```

The parameter size means the input data size (GB)

You can find the generated text data in hdfs:/hadoop/terasort/terasort-{size}G

Step 4. Run the workload

```
$ ./run-terasort.sh <size>
```

The parameter size means the input data size (GB)

Step 5. Collect the running results

The output of the workload will be put in hdfs with location /hadoop/terasort/terasort-out.

2) Spark based

Step 1. Required Software

Spark stack and BGDS

Step 2. Get workloads from BigDataBench

Download the benchmark package from

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz

Step 3. Decompress the Spark package.

```
$ tar -zxvf BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz
```

Step 4. Prepare the input

```
$ cd BigDataBench_V5.0_BigData_MicroBenchmark/
$ cd Spark/Sort
$ ./genData-Sort.sh <size>
```

The parameter size means the input data size (GB)

You can find the generated text data in hdfs: /spark/sort/sort-{size}G

Step 5. Run the workload

```
$ ./runSpark-Sort.sh <size>
```

The parameter size means the input data size (GB)

Step 6. Collect the running results

The output of the workload will be put in hdfs with location /spark/sort/output.

3) Flink based

Required Software Stacks Flink and BGDS

Step 1. Get workloads from BigDataBench

Download the benchmark package from

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz

Step 2. Decompress the Hadoop package.

```
$ tar -zxvf BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz
```

Install gsl：

```
$ cd BigDataBench_V5.0_BigData_MicroBenchmark/
$ ./prepar.sh
```

Step 3. Prepare the input

```
$ cd Flink/sort-grep-wc
$./genData_MicroBenchmarks.sh
```

Then you need to input the data size (GB) you want to generate – “print data size GB”. The data will be generated in /data-MicroBenchmarks directory on HDFS.

Step 4. Run the workload

```
$ ./run_Microbenchmarks.sh <workload>
```

The workload can be “Sort/Grep/Wordcount”.

Step 5. Collect the running results

The output of the workload will be put in hdfs with location /flink-xxx-result.

4) MPI based

Step 1. Required software stacks

MPICH2

Step 2. Get MPI workload from BigDataBench

Download from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz

Step 3. Prepare the input

The data sets used by these four workloads are generated by big data generation tool (BDGS).

To generate data:

i) Unpack the downloaded tar file

```
$ tar -zxvf BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz
```

ii) Generate data for Sort:

```
$ cd BigDataBench_V5.0_BigData_MicroBenchmark/MPI/MPI_Sort
$ ./genData_Sort.sh
```

iii) Generate data for Grep:

```
$ cd BigDataBench_V5.0_BigData_MicroBenchmark/MPI/MPI_Grep
$ sh genData_grep.sh
```

iv) Generate data for WordCount:

```
$ cd BigDataBench_V5.0_BigData_MicroBenchmark/MPI/MPI_WordCount
$ sh genData_wordcount.sh
```

v) Generate data for MD5:

```
$ cd BigDataBench_V5.0_BigData_MicroBenchmark/MPI/MPI_MD5
$ sh genData_md5.sh
```

Input the data size you want to generate with the units of GB, such as 10 if you want to generat 10 GB data. After this step, it will generate data under respective directory.

Step 4. Run the workload

i) Install workload

```
$ cd BigDataBench_V5.0_BigData_MicroBenchmark/
$ cdMPI/MPI_Sort(/Grep/WordCount/MD5)
$ make
```

After this step, there will be one executable files named mpi_sort(/grep/wordcount/md5) under the current directory. Then you can run the workload.

ii) For Sort, command is:

```
$mpirun -f machine_file -n PROCESS_NUM ./mpi_sort input_file output_file
```

iii) For Grep, command is:

```
$mpirun -f machine_file -n PROCESS_NUM ./mpi_grep input_file pattern
```

iv) For WordCount, command is:

```
$mpirun -f machine_file -n PROCESS_NUM ./mpi_wordcount input_file
```

iv) For MD5, command is:

```
$mpirun -f machine_file -n PROCESS_NUM ./mpi-md5 input_file output_file
```

For example, the three command would be:

```
$mpirun -f machine_file -n 12 ./mpi_sort data-sort/in output
$mpirun -f machine_file -n 12 ./mpi_grep data-grep/in abc
$mpirun -f machine_file -n 12 ./mpi_wordcount data-wordcount/in
```

Step 5. Collect the running results

When the workload run is complete, it will display the running information, such as: Total running time:5.000000 sec

Note that if you want to collect the performance data on system or architecture level, you should run corresponding scripts in the background to collect data.

Note: For grep workload, the second parameter (pattern) in running command line means the expression needs to be matched.

4.2.2 Connected Component (CC)

1) Hadoop based

Required Software Stacks Hadoop and BGDS

Step 1. Get workloads from BigDataBench

Download the benchmark package from http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz

Step 2. Decompress the Hadoop package.

```
$ tar -zxvf BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz
$ cd BigDataBench_V5.0_BigData_MicrBenchmark
```

Step 3. Prepare the input

```
$ cd Hadoop/CC
$./genData-cc.sh <log_vertex>
```

The parameter log_vertex indicates the vertex of the generated data, means vertex = 2^log_vertex.

You can find the generated graph data is under the hdfs directory: /hadoop/cc

Step 4. Run the workload

```
$ ./run-cc.sh <log_vertex>
```

The parameter log_vertex indicates the vertex of the generated data, means vertex = 2^log_vertex.

Step 5. Collect the running results

The output of the workload will be put in hdfs: concmpt_curbm, concmpt_tempbm, concmpt_nextbm, concmpt_output.

2) Spark based

Step 1. Required Software

Spark stack and BGDS

Step 2. Get workloads from BigDataBench

Download the benchmark package from http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz

Step 3. Decompress the Spark package.

```
$ tar -zxvf BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz
$ cd BigDataBench_V5.0_BigData_MicroBenchmark
```

Step 4. Prepare the input

```
$ cd Spark/CC
$ ./genData-cc.sh <log_vertex>
```

The parameter log_vertex indicates the vertex of the generated data, means vertex = 2^log_vertex.

You can find the generated graph data is under the hdfs directory: /spark/cc

Step 5. Run the workload

$ ./runSpark-cc.sh <log_vertex>

The parameter log_vertex indicates the vertex of the generated data, means vertex = 2^log_vertex.

Step 6. Collect the running results

Note that if you want to collect the performance data on system or architecture level, you should run corresponding scripts in the background to collect data.

3) MPI based

Step 1. Required software stacks

MPICH2

Cmake: Cmake 2.8.12.2 is preferred

Boost 1.43.0

When you install the boost packet, make sure that the mpi packet has been installed.

```
$sh bootstrap.sh
$./bjam
```

Building parallel-bgl-0.7.0:

```
$ cd BigDataBench_V5.0_MPI/MicroBenchmark/GraphAnalytics
$ cd ConnectedComponent/parallel-bgl-0.7.0
$ cmake ./
$ cd parallel-bgl-0.7.0/libs/graph_parallel/test
$ make distributed_page_rank_test
```

Step 2. Get MPI workload from BigDataBench

Download from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz

Step 3. Prepare the input

The data set used by CC is generated by big data generation tool (BDGS).

To generate data:

i) Unpack the downloaded tar file

```
$ tar -zxvf BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz
```

ii) Generate data for CC:

```
$ cd BigDataBench_V5.0_BigData_MicroBenchmark/MPI/MPI_Connect
$ ./genData_connectedComponents.sh
```

Then you will be asked how many data you like to generate:

Please Enter The Iterations of GenGragh: (enter a number here, It means the number of vertices generated, represented by power of 2)

You can find the generated graph data: data-Connected_Components/Facebook_genGragh_$I.txt ($I here is the number you entered).

Step 4. Run the workload

Run through linux command:

```
$ mpirun -f machine_file -n PROCESS_NUM ./run_connectedComponents InputGraphfile num_ofVertex num_ofEdges
```

Note that you can find the num_ofVertex and num_ofEdges information from the output of the data generating command.

Step 5. Collect the running results

If you want to collect the performance data on system or architecture level, you should run corresponding scripts in the background to collect data.

4.2.3 RandSample

1) Hadoop based

Required Software Stacks Hadoop and BGDS

Step 1. Get workloads from BigDataBench

Download the benchmark package from http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz

Step 2. Decompress the Hadoop package.

```
$ tar -zxvf BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz
```

Install gsl：

```
$ cd BigDataBench_V5.0_BigData_MicroBenchmark/
$ ./prepar.sh
```

Step 3. Prepare the input

```
$ cd Hadoop/randSample
$./genData-randSample.sh <size>
```

The parameter size means the input data size (GB).

You can find the generated text data in hdfs:/hadoop/randsample/{size}GB-randsampleHP

Step 4. Run the workload

```
$ ./run-randSample.sh <size> <sample_ratio>
```

Parameter size: the input data size, GB

Parameter sample_ratio: the sampling ratio, ranges from 0 to 1.

Step 5. Collect the running results

The output of the workload will be put in hdfs with location /hadoop/randsample/randsampleHP-result.

2) Spark based

Step 1. Required Software

Spark stack and BGDS

Step 2. Get workloads from BigDataBench

Download the benchmark package from http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz

Step 3. Decompress the Spark package.

```
$ tar -zxvf BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz
```

Step 4. Prepare the input

```
$ cd BigDataBench_V5.0_BigData_MicroBenchmark/
$ cd Spark/randSample
$ ./genData-randSample.sh <size>
```

The parameter size means the input data size (GB).

You can find the generated text data in hdfs: /spark/randsample/

Step 5. Run the workload

`$ ./runSpark-randSample.sh <size> <sample_ratio>`

Parameter size: the input data size, GB

Parameter sample_ratio: the sampling ratio, ranges from 0 to 1.

Step 6. Collect the running results

The output of the workload will be put in hdfs with location /spark/randsample/output.

3) MPI based

Step 1. Required software stacks

MPICH2

Step 2. Get MPI workload from BigDataBench

Download from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz

Step 3. Prepare the input

The data sets used by these four workloads are generated by big data generation tool (BDGS).

To generate data:

i) Unpack the downloaded tar file

```
$ tar -zxvf BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz
```

ii) Generate data for Sort:

```
$ cd BigDataBench_V5.0_BigData_MicroBenchmark/MPI/mpiRandSample
$ sh genData_randsample.sh
```

Input the data size you want to generate with the units of GB, such as 10 if you want to generat 10 GB data. After this step, it will generate data under RandSample directory.

Step 4. Run the workload

i) Install workload

```
$ cd BigDataBench_V5.0_BigData_MicroBenchmark/MPI/mpiRandSample
$ make
```

After this step, there will be one executable files named mpi-randsample under the current directory. Then you can run the workload.

ii) Run the workload

```
$mpirun -f machine_file -n PROCESS_NUM ./mpi-randsample input_file output_file sample_ratio
```

Step 5. Collect the running results

When the workload run is complete, it will generate the output_file.

Note that if you want to collect the performance data on system or architecture level, you should run corresponding scripts in the background to collect data.

4.2.3 FFT

1) Hadoop based

Required Software Stacks Hadoop and BGDS

Step 1. Get workloads from BigDataBench

Download the benchmark package from
http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_Micro_Benchmark.tar.gz

Step 2. Decompress the Hadoop package.

$ tar -zxvf BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz

Install gsl：

$ cd BigDataBench_V5.0_BigData_MicroBenchmark/
$ ./prepar.sh

Step 3. Prepare the input

$ cd Hadoop/FFT
$./genData-fft.sh <row_num> <col_num> <sparsity>

"sparsity" ranges from 0 to 1, which means the ratios that the matrix elements are zero. 0 represents no element is zero while 1 represents all elements are zero.

After the run process, it will generate the input data on HDFS under directory: /hadoop/fft/

Step 4. Run the workload

$ ./run-fft.sh <row_num> <col_num> <sparsity>

The parameters are the same with the generating command.

Step 5. Collect the running results

The output of the workload will be put in hdfs with location /hadoop/fft/fft-result.

2) Spark based

Step 1. Required Software

Spark stack and BGDS

Step 2. Get workloads from BigDataBench

Download the benchmark package from
http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz

Step 3. Decompress the Spark package.

$ tar -zxvf BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz

Step 4. Prepare the input

$ cd BigDataBench_V5.0_BigData_MicroBenchmark/
$ cd Spark/FFT
$./genData-fft.sh <row_num> <col_num> <sparsity>

"sparsity" ranges from 0 to 1, which means the ratios that the matrix elements are zero. 0 represents no element is zero while 1 represents all elements are zero.

After the run process, it will generate the input data on HDFS under directory: /spark/fft/

Step 5. Run the workload

$ ./runSpark-fft.sh <row_num> <col_num> <sparsity>

The parameters are the same with the generating command.

Step 6. Collect the running results

The output of the workload will be put in hdfs with location /spark/fft/output.

3) MPI based

Step 1. Required software stacks

MPICH2

Step 2. Get MPI workload from BigDataBench

Download from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz

Step 3. Prepare the input

The data sets used by these four workloads are generated by big data generation tool (BDGS).

To generate data:

i) Unpack the downloaded tar file

```
$ tar -zxvf BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz
```

ii) Generate data for fft:

```
$ cd BigDataBench_V5.0_BigData_MicroBenchmark/MPI/mpiFFT
$ sh genData-fft.sh <row_num> <col_num> <sparsity>
```

"sparsity" ranges from 0 to 1, which means the ratios that the matrix elements are zero. 0 represents no element is zero while 1 represents all elements are zero.

After the run process, it will generate the input data: genData-Matrix/fft-data

Step 4. Run the workload

i) Install workload

```
$ cd BigDataBench_V5.0_BigData_MicroBenchmark/MPI/mpiFFT
$ make
```

After this step, there will be one executable files named mpifft under the current directory. Then you can run the workload.

ii) Run the workload

```
$mpirun -f machine_file -n PROCESS_NUM ./mpifft genData-Matrix/fft-data
```

Step 5. Collect the running results

Note that if you want to collect the performance data on system or architecture level, you should run corresponding scripts in the background to collect data.

4.2.4 Matrix Multiply

1) Hadoop based

Required Software Stacks Hadoop and BGDS

Step 1. Get workloads from BigDataBench

Download the benchmark package from

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz

Step 2. Decompress the Hadoop package.

```
$ tar -zxvf BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz
```

Step 3. Prepare the input

```
$ cd BigDataBench_V5.0_BigData_MicroBenchmark/Hadoop/MatrixMult
$./genData-matMult.sh <sparsity> <row_i> <col_i> <col_j>
```

sparsity: the percentage of zero elements, ranges from 0 to 1.

row_i: the row number of matrix A

col_i: the column number of matrix A
col_j: the column number of matrix B
After the run process, it will generate the input data on HDFS under directory: /hadoop/matMult/mat1 and /hadoop/matMult/mat2

Step 4. Run the workload

```
$ ./run-matMult.sh <sparsity> <row_i> <col_i> <col_j>
```

sparsity: the percentage of zero elements, ranges from 0 to 1.
row_i: the row number of matrix A
col_i: the column number of matrix A
col_j: the column number of matrix B

Step 5. Collect the running results

The output of the workload will be put in hdfs with location /hadoop/matMult/mat-out.

2) Spark based

Step 1. Required Software

Spark stack and BGDS

Step 2. Get workloads from BigDataBench

Download the benchmark package from
http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz

Step 3. Decompress the Spark package.

```
$ tar -zxvf BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz
```

Step 4. Run the workload

The workload use random generate dataset, so we don't need to generate data by ourselves.

```
$ ./runSpark_matMult.sh <row_i> <col_i> <col_j>
```

row_i: the row number of matrix A
col_i: the column number of matrix A
col_j: the column number of matrix B

Step 5. Collect the running results

Note that if you want to collect the performance data on system or architecture level, you should run corresponding scripts in the background to collect data.

4.2.5 Select Query, Aggregation Query, Join Query

1) Hive based

Step 1. Required Software Stacks

Java JDK: version 1.6 or later
Hadoop: we recommend version 2.7.1, which was used and tested in our environment.
Hive: we recommend version 1.2.1, which was used and tested in our environment.

Step 2. Get workloads from BigDataBench

Download the benchmark package from

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz

Step 3. Prepare the input

Make sure Hadoop and Hive have been successfully started.

Unpack the downloaded tar file:

```
$tar -xzvf BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz
$cd BigDataBench_V5.0_BigData_MicroBenchmark
$ cd Hive/Interactive_Query
$ ./gen_data.sh
```

Step 4. Run the workloads;

```
$ ./run_AnalysiticWorkload.sh
```

The information of selecting workload will be printed on the screen:

Please select a number to choose the corresponding Workload algorithm

1. aggregation Workload
2. join Workload
3. select Workload

Enter your choice :

For example, we enter 1 to select aggregation Workload.

Step 5. Collect the running results

When the workload run complete, it will display the running information, such as:

ok. You chose 1 and we'll use aggregation Workload

WARNING: org.apache.hadoop.metrics.jvm.EventCounter is deprecated. Please use org.apache.hadoop.log.metrics.EventCounter in all the log4j.properties files.

Logging initialized using configuration in jar:file:/usr/local/hadoop/ hive-0.9.0/lib/hive-common-0.9.0.jar!/hive-log4j.properties Hive history file=/tmp/root/hive_job_log_root_201510032145_767144040.txt OK

Time taken: 4.183 seconds

Total MapReduce jobs = 1

Launching Job 1 out of 1

Number of reduce tasks not specified. Estimated from input data size:

1

In order to change the average load for a reducer (in bytes):

set hive.exec.reducers.bytes.per.reducer=<number>

In order to limit the maximum number of reducers:

set hive.exec.reducers.max=<number>

In order to set a constant number of reducers:

set mapred.reduce.tasks=<number>

Starting Job = job_201509190338_0009, Tracking URL = http://localhost:

50030/jobdetails.jsp?jobid=job_201509190338_0009

Kill Command = /usr/local/hadoop/hadoop-1.2.1/libexec/../bin/hadoop job -Dmapred.job.tracker=localhost:9001 -kill job_201509190338_0009 Hadoop job information for Stage-1: number of mappers: 0; number of reducers: 1

2015-10-03 21:45:59,452 Stage-1 map = 02015-10-03 21:46:06,489 Stage-1 map = 02015-10-03 21:46:09,512 Stage-1 map = 100MapReduce Total cumulative CPU time: 4 seconds 80 msec

Ended Job = job_201509190338_0009
Moving data to: hdfs://localhost:9000/user/hive/warehouse/tmp27
Table default.tmp27 stats: [num_partitions: 0, num_files: 1, num_rows: 0, total_size: 0, raw_data_size: 0]
MapReduce Jobs Launched:
Job 0: Reduce: 1 Cumulative CPU: 4.08 sec HDFS Read: 0 HDFS Write: 0 SUCCESS
Total MapReduce CPU Time Spent: 4 seconds 80 msec
OK
Time taken: 21.116 seconds

2) Impala version

Step 1. Required Software Stacks

CentOS: 6.5
Java JDK: version 1.6 or later
Hadoop: hadoop-2.0.0-cdh4.2.0
Hive: hive-0.10.0-cdh4.2.0
MySQL: 5.1.73

Step 2. Get workloads from BigDataBench

Download the Benchmark from this link:
http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz

Step 3. Prepare the input

Make sure Hadoop, Hive and Impala have been successfully started.

Here we use Aggregation workload as an example, the others are the same under respective directory.

Unpack the downloaded tar file:

```
$ tar -xzvf BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz
$ cd BigDataBench_V5.0_BigData_MicroBenchmark
$ cd Impala/Interactive_Query
```

Then execute gen_data.sh:

```
$ ./gen_data.sh
```

The information of selecting data size will be printed on the screen:
print data size GB :
For example, we enter 1 to select 1GB data.

Step 4. Run the workload

Modify impala_restart.sh, replace your impala node with actual impala node ip. For example,

```
for i in localhost
```

Run the workloads;

```
$ ./run_AnalysiticWorkload.sh
```

Step 5. Collect the running results

When the workload run is complete, it will display the running information, such as:

Logging initialized using configuration in file:/home/cdh4/hive-0.10.0-cdh4.2.0/
Hive history file=/tmp/root/hive_job_log_root_201510040942_192414277.txt
SLF4J: Class path contains multiple SLF4J bindings.
SLF4J: Found binding in [jar:file:/home/renrui/cdh4/hadoop-2.0.0-cdh4.2.0/share/hadoop/c
SLF4J: Found binding in [jar:file:/home/cdh4/hive-0.10.0-cdh4.2.0/lib/slf4j-log4j
SLF4J: See http://www.slf4j.org/codes.html#multiple_bindings for an explanation.
OK
Time taken: 3.727 seconds
OK
Time taken: 0.363 seconds

4.2.6 Aggregation, Cross Product, Difference, Filter, OrderBy, Project, Union

1) Hive version

Step 1. Required Software Stacks

Java JDK: version 1.6 or later

Hadoop: we recommend version 2.7.1, which was used and tested in our environment.

Hive: we recommend version 1.2.1, which was used and tested in our environment.

Step 2. Get workloads from BigDataBench

Download the benchmark package from
http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz

Step 3. Prepare the input

Make sure Hadoop and Hive have been successfully started.

Unpack the downloaded tar file:

```
$ tar -xzvf BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz
$ cd BigDataBench_V5.0_BigData_MicroBenchmark
$ cd Hive/Interactive_MicroBenchmark
$ ./gen_data.sh
```

Step 4. Run the workload

```
$ ./run_MicroBenchmarks.sh
```

The information of selecting workload will be printed on the screen:

Please select a number to choose the corresponding Workload algorithm

1. aggregationAVG Workload
2. aggregationMAX Workload
3. aggregationMIN Workload
4. aggregationSUM Workload
5. crossproject Workload
6. difference Workload
7. filter Workload
8. orderby Workload
9. projection Workload

10. union Workload
Enter your choice:
For example, we enter 5 to select crossproject Workload.

Step 5. Collect the running results

When the workload run is complete, it will display the running information, such as:

ok. You chose 5 and we'll use crossproject Workload
WARNING: org.apache.hadoop.metrics.jvm.EventCounter is deprecated. Please use org.apache.hadoop.log.metrics.EventCounter in all the log4j.properties files.
Logging initialized using configuration in jar:file:/usr/local/hadoop/hive - 0.9.0/lib/hive-common-0.9.0.jar!/hive-log4j.properties
Hive history file=/tmp/root/hive_job_log_root_201509190403_2134444140.txt OK
Time taken: 4.117 seconds
Total MapReduce jobs = 1
Launching Job 1 out of 1
Number of reduce tasks not specified. Estimated from input data size:
1
In order to change the average load for a reducer (in bytes):
set hive.exec.reducers.bytes.per.reducer=<number>
In order to limit the maximum number of reducers:
set hive.exec.reducers.max=<number>
In order to set a constant number of reducers:
set mapred.reduce.tasks=<number>
Starting Job = job_201509190338_0006, Tracking URL = http://localhost:50030 /jobdetails.jsp?jobid=job_201509190338_0006 Kill Command = /usr/local /hadoop/hadoop-1.2.1/libexec/../bin/hadoop job -Dmapred.job.tracker= localhost:9001 -kill job_201509190338_0006
Hadoop job information for Stage-1: number of mappers: 0; number of
reducers: 1
2015-09-19 04:04:12,519 Stage-1 map = 02015-09-19 04:04:20,569 Stage-1 map = 02015-09-19 04:04:23,600 Stage-1 map = 100MapReduce Total cumulative CPU time: 4 seconds 130 msec
Ended Job = job_201509190338_0006 Moving data to: hdfs://localhost:9000/user/hive/wareho
Table default.tmp33 stats: [num_partitions: 0, num_files: 1, num_rows:
0, total_size: 0, raw_data_size: 0]
MapReduce Jobs Launched:
Job 0: Reduce: 1 Cumulative CPU: 4.13 sec HDFS Read: 0 HDFS Write: 0
SUCCESS
Total MapReduce CPU Time Spent: 4 seconds 130 msec
OK
Time taken: 22.31 seconds

2) Impala version

Step 1. Required Software Stacks

CentOS: 6.5

Java JDK: version 1.6 or later

Hadoop: hadoop-2.0.0-cdh4.2.0

Hive: hive-0.10.0-cdh4.2.0

MySQL: 5.1.73

Step 2. Get workloads from BigDataBench

Download the Benchmark from this link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz

Step 3. Prepare the input

Make sure Hadoop, Hive and Impala have been successfully started.

Unpack the downloaded tar file:

```
$tar -xzvf BigDataBench_V5.0_BigData_MicroBenchmark.tar.gz
$cd BigDataBench_V5.0_BigData_MicroBenchmark
$ cd Impala/Interactive_MicroBenchmark
$ ./gen_data.sh
```

Step 4. Run the workload

Modify impala_restart.sh, replace your impala node with actual impala node ip. For example,

```
for i in localhost
```

Run the workloads;

```
$ ./run_MicroBenchmark.sh
```

Step 5. Collect the running results

When the workload run is complete, it will display the running information, such as:

The information of selecting workload will be printed on the screen:

Logging initialized using configuration in
file:/home/renrui/cdh4/hive-0.10.0-cdh4.2.0/conf/hive-log4j.properties
Hive history file=/tmp/root/hive_job_log_root_201510031047_550088197.txt
SLF4J: Class path contains multiple SLF4J bindings. SLF4J: Found binding
in [jar:file:/home/renrui/cdh4/hadoop-2.0.0-cdh4.2.0/share/hadoop/common
/lib/slf4j-log4j12-1.6.1.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: Found binding in [jar:file:/home/renrui/cdh4/hive-0.10.0-cdh4.2.0
/lib/slf4j-log4j12-1.6.1.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: See http://www.slf4j.org/codes.html#multiple_bindings for an
explanation.
OK
Time taken: 3.672 seconds
OK
Time taken: 0.365 seconds

4.2.7 Convolution

1) TensorFlow based

Step 1. Required Software Stacks

Python 2 or 3
Scipy and Numpy
TensorFlow 1.0+

Step 2. Get workloads from BigDataBench

Download the Benchmark from the link:
http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_MicroBenchmark.tar.gz

Step 3. Prepare the input

The TensorFlow micro benchmarks use random generate data, you need to specify the ***batch size***, ***image size***, ***channel***, and ***filter size***.

Step 4. Run the workloads;

```
$ tar –xf BigDataBench_V5.0_AI_MicroBenchmark.tar.gz
$ cd BigDataBench_V5.0_AI_MicroBenchmark/TensorFlow
$ python conv2d.py <batch_size> <img_size> <channel> <filter_size>
```

Running conv2d with scripts:

```
$ ./run-tensorflow.sh conv <datasize>
```

Parameter “datasize” can be large/medium/small.
large: 224*224*64 (means length, width and channel respectively)
medium: 112*112*128
small: 56*56*256

Step 5. Collect the running results

When the workload run complete, it will display the running time information.

2) Pthreads based

Step 1. Required Software Stacks

g++ compiler
OpenCV, recommend 3.2 version
Dependences: libopencv_core.so.3.2 and libopencv_imgproc.so.3.2

Step 2. Get workloads from BigDataBench

Download the Benchmark from this link:
http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_MicroBenchmark.tar.gz

Step 3. Prepare the input

```
$ cd BigDataBench_V5.0_AI_MicroBenchmark/Pthread
```

The Pthread micro benchmarks use ImageNet as data input, *ImageData* directory contains the image data with three sizes: Image_1000, Image_10000 and Image_100000.

Step 4. Compile the workload

```
$ make
```

This command will produce an executable file named conv2d.

Step 5. Run the workload

```
$ ./conv2d ../ImageData/image_$imgsize/img$imgsize/ NCHW 12 227 227 100
```

Here $imgsize can be 1000, 10000, or 100000.

Step 6. Collect the running results

When the workload run is complete, it will display the output.

4.2.8 Fully Connected

1) TensorFlow based

Step 1. Required Software Stacks

Python 2 or 3
Scipy and Numpy
TensorFlow 1.0+

Step 2. Get workloads from BigDataBench

Download the Benchmark from the link:
http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_MicroBenchmark.tar.gz

Step 3. Prepare the input

The TensorFlow micro benchmarks use random generate data, you need to specify the ***batch size***, ***image size***, and ***channel***.

Step 4. Run the workloads;

```
$ tar –xf BigDataBench_V5.0_AI_MicroBenchmark.tar.gz
$ cd BigDataBench_V5.0_AI_MicroBenchmark/TensorFlow
$ python matmul.py <batch_size> <img_size> <channel>
```

Running fully connected with scripts:

```
$ ./run-tensorflow.sh matmul <datasize>
```

Parameter “datasize” can be large/medium/small.
large: 224*224*64 (means length, width and channel respectively)
medium: 112*112*128
small: 56*56*256

Step 5. Collect the running results

When the workload run complete, it will display the running time information.

2) Pthreads based

Step 1. Required Software Stacks

g++ compiler
OpenCV, recommend 3.2 version
Dependences: libopencv_core.so.3.2 and libopencv_imgproc.so.3.2

Step 2. Get workloads from BigDataBench

Download the Benchmark from this link:
http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_MicroBenchmark.tar.gz

Step 3. Prepare the input

```
$ cd BigDataBench_V5.0_AI_MicroBenchmark/Pthread
```

The Pthread micro benchmarks use ImageNet as data input, *ImageData* directory contains the image data with three sizes: Image_1000, Image_10000 and Image_100000.

Step 4. Compile the workload

```
$ make
```

This command will produce an executable file named matmul.

Step 5. Run the workload

```
$ ./matmul ../ImageData/image_$imgsize/img$imgsize/ 12 227 227 100
```

Here $imgsize can be 1000, 10000, or 100000.

Step 6. Collect the running results

When the workload run is complete, it will display the output.

4.2.9 Relu, Sigmoid, Tanh

We use the Relu as an example, the running processes of Sigmoid and Tanh are the same, you can just change the relu in the command to sigmoid or tanh.

1) TensorFlow based

Step 1. Required Software Stacks

Python 2 or 3
Scipy and Numpy
TensorFlow 1.0+

Step 2. Get workloads from BigDataBench

Download the Benchmark from the link:
http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_MicroBenchmark.tar.gz

Step 3. Prepare the input

The TensorFlow micro benchmarks use random generate data, you need to specify the ***batch size***, ***image size***, and ***channel***.

Step 4. Run the workloads;

```
$ tar –xf BigDataBench_V5.0_AI_MicroBenchmark.tar.gz
$ cd BigDataBench_V5.0_AI_MicroBenchmark/TensorFlow
$ python relu.py <batch_size> <img_size> <channel>
```

Running relu/sigmoid/tanh with scripts:

```
$ ./run-tensorflow.sh <workload> <datasize>
```

Parameter “workload” can be relu/sigmoid/tanh.
Parameter “datasize” can be large/medium/small.
large: 224*224*64 (means length, width and channel respectively)
medium: 112*112*128
small: 56*56*256

Step 5. Collect the running results

When the workload run complete, it will display the running time information.

2) Pthreads based

Step 1. Required Software Stacks

g++ compiler

OpenCV, recommend 3.2 version

Dependences: libopencv_core.so.3.2 and libopencv_imgproc.so.3.2

Step 2. Get workloads from BigDataBench

Download the Benchmark from this link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_MicroBenchmark.tar.gz

Step 3. Prepare the input

```
$ cd BigDataBench_V5.0_AI_MicroBenchmark/Pthread
```

The Pthread micro benchmarks use ImageNet as data input, *ImageData* directory contains the image data with three sizes: Image_1000, Image_10000 and Image_100000.

Step 4. Compile the workload

```
$ make
```

This command will produce an executable file named relu, sigmoid or tanh.

Step 5. Run the workload

```
$ ./relu ../ImageData/image_$imgsize/img$imgsize/ 12 227 227 100
```

Here $imgsize can be 1000, 10000, or 100000.

Step 6. Collect the running results

When the workload run is complete, it will display the output.

4.2.10 MaxPooling, AvgPooling

We use the MaxPooling as an example, the running process of AvgPooling is the same, you can just change the max_pool in the command to avg_pool.

1) TensorFlow based

Step 1. Required Software Stacks

Python 2 or 3

Scipy and Numpy

TensorFlow 1.0+

Step 2. Get workloads from BigDataBench

Download the Benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_MicroBenchmark.tar.gz

Step 3. Prepare the input

The TensorFlow micro benchmarks use random generate data, you need to specify the ***batch size***, ***image size***, and ***channel***.

Step 4. Run the workloads;

```
$ tar –xf BigDataBench_V5.0_AI_MicroBenchmark.tar.gz
$ cd BigDataBench_V5.0_AI_MicroBenchmark/TensorFlow
$ python max_pool.py <batch_size> <img_size> <channel>
```

Running MaxPooling and AvgPooling with scripts:

```
$ ./run-tensorflow.sh <workload> <datasize>
```

Parameter “workload” can be maxpool or avgpool.

Parameter "datasize" can be large/medium/small.
large: 224*224*64 (means length, width and channel respectively)
medium: 112*112*128
small: 56*56*256

Step 5. Collect the running results

When the workload run complete, it will display the running time information.

2) Pthreads based

Step 1. Required Software Stacks

g++ compiler
OpenCV, recommend 3.2 version
Dependences: libopencv_core.so.3.2 and libopencv_imgproc.so.3.2

Step 2. Get workloads from BigDataBench

Download the Benchmark from this link:
http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_MicroBenchmark.tar.gz

Step 3. Prepare the input

```
$ cd BigDataBench_V5.0_AI_MicroBenchmark/Pthread
```

The Pthread micro benchmarks use ImageNet as data input, *ImageData* directory contains the image data with three sizes: Image_1000, Image_10000 and Image_100000.

Step 4. Compile the workload

```
$ make
```

This command will produce an executable file named max_pool or avg_pool.

Step 5. Run the workload

```
$ ./max_pool ../ImageData/image_$imgsize/img$imgsize/ 12 227 227 100
```

Here $imgsize can be 1000, 10000, or 100000.

Step 6. Collect the running results

When the workload run is complete, it will display the output.

4.2.11 CosineNorm, BatchNorm

We use the BatchNorm as an example, the running process of CosineNorm is the same, you can just change the batch_norm in the command to cosine_norm.

1) TensorFlow based

Step 1. Required Software Stacks

Python 2 or 3
Scipy and Numpy
TensorFlow 1.0+

Step 2. Get workloads from BigDataBench

Download the Benchmark from the link:
http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_MicroBenchmark.tar.gz

Step 3. Prepare the input

The TensorFlow micro benchmarks use random generate data, you need to specify the ***batch size***, ***image size***, and ***channel***.

Step 4. Run the workloads;

```
$ tar –xf BigDataBench_V5.0_AI_MicroBenchmark.tar.gz
$ cd BigDataBench_V5.0_AI_MicroBenchmark/TensorFlow
$ python batch_normalization.py <batch_size> <img_size> <channel>
```

Running batchNorm with scripts:

```
$ ./run-tensorflow.sh batchNorm <datasize>
```

Parameter “datasize” can be large/medium/small.

large: 224*224*64 (means length, width and channel respectively)

medium: 112*112*128

small: 56*56*256

Step 5. Collect the running results

When the workload run complete, it will display the running time information.

2) Pthreads based

Step 1. Required Software Stacks

g++ compiler

OpenCV, recommend 3.2 version

Dependences: libopencv_core.so.3.2 and libopencv_imgproc.so.3.2

Step 2. Get workloads from BigDataBench

Download the Benchmark from this link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_MicroBenchmark.tar.gz

Step 3. Prepare the input

```
$ cd BigDataBench_V5.0_AI_MicroBenchmark/Pthread
```

The Pthread micro benchmarks use ImageNet as data input, *ImageData* directory contains the image data with three sizes: Image_1000, Image_10000 and Image_100000.

Step 4. Compile the workload

```
$ make
```

This command will produce an executable file named batch_norm.

Step 5. Run the workload

```
$ ./batch_norm ../ImageData/image_$imgsize/img$imgsize/ 12 227 227 100
```

Here $imgsize can be 1000, 10000, or 100000.

Step 6. Collect the running results

When the workload run is complete, it will display the output.

4.2.12 Dropout

1) TensorFlow based

Step 1. Required Software Stacks

Python 2 or 3

Scipy and Numpy

TensorFlow 1.0+

Step 2. Get workloads from BigDataBench

Download the Benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_MicroBenchmark.tar.gz

Step 3. Prepare the input

The TensorFlow micro benchmarks use random generate data, you need to specify the ***batch size***, ***image size***, and ***channel***.

Step 4. Run the workloads;

```
$ tar –xf BigDataBench_V5.0_AI_MicroBenchmark.tar.gz
$ cd BigDataBench_V5.0_AI_MicroBenchmark/TensorFlow
$ python dropout.py <batch_size> <img_size> <channel>
```

Running fully connected with scripts:

```
$ ./run-tensorflow.sh dropout <datasize>
```

Parameter “datasize” can be large/medium/small.

large: 224*224*64 (means length, width and channel respectively)

medium: 112*112*128

small: 56*56*256

Step 5. Collect the running results

When the workload run complete, it will display the running time information.

2) Pthreads based

Step 1. Required Software Stacks

g++ compiler

OpenCV, recommend 3.2 version

Dependences: libopencv_core.so.3.2 and libopencv_imgproc.so.3.2

Step 2. Get workloads from BigDataBench

Download the Benchmark from this link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_MicroBenchmark.tar.gz

Step 3. Prepare the input

```
$ cd BigDataBench_V5.0_AI_MicroBenchmark/Pthread
```

The Pthread micro benchmarks use ImageNet as data input, *ImageData* directory contains the image data with three sizes: Image_1000, Image_10000 and Image_100000.

Step 4. Compile the workload

```
$ make
```

This command will produce an executable file named dropout.

Step 5. Run the workload

```
$ ./dropout ../ImageData/image_$imgsize/img$imgsize/ 12 227 227 100
```

Here $imgsize can be 1000, 10000, or 100000.

Step 6. Collect the running results

When the workload run is complete, it will display the output.

4.3 Component Benchmarks

Considering the benchmarking scalability, we use the motif combinations to compose original complex workloads with a DAG-like structure considering the data pipeline. The DAG-like structure is to use a node representing original or intermediate data set being processed, and an edge representing a data motif.

4.3.1 Image Classification

1) TensorFlow based

Step 1. Required Software Stacks

1. tensorflow-gpu 1.12 or tensorflow 1.12
   $pip install tensorflow-gpu==1.12 or pip install tensorflow==1.12
   if you want to build tensorflow from source, see
   https://www.tensorflow.org/install/source
2. Cuda 9.0
   Downloads cuda9.0: https://developer.nvidia.com/cuda-90-download-archive
   Installation guide for linux: https://docs.nvidia.com/cuda/cuda-installation-guide-linux/index.html
3. Cudnn 7.4.2
   Downloads cudnn 7.4.2: https://developer.nvidia.com/cudnn
   Installation guide for linux: https://docs.nvidia.com/deeplearning/sdk/cudnn-install/index.html

Step 2. Get workloads from BigDataBench

Download the Benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz

```
$ tar –xf BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_AI_ComponentBenchmark/
$ cd TensorFlow/Image_classification
```

Step 3. Prepare the input

1. Download ImageNet ILSVRC2012 Dataset from http://www.image-net.org/
2. Convet these raw images to TFRecords by using build_imagenet_data.py script.

Step 4. Run the workloads

```
$python imagenet_main.py –data_dir=/path/to/imagenet
```

Both the training dataset and the validation dataset are in the same directory. The model will begin training and will automatically evaluate itself on the validation data roughly once per epoch.

Some running options:

--model_dir: to choose where to store the model

--resnet_size: to choose the model size (options include ResNet-18 through ResNet-200)

--num-gpus: to choose computing device

0: Use OneDeviceStrategy and train on CPU
1: Use OneDeviceStrategy and train on GPU
2+: Use Mirroredstrategy (data parallelism) to distribute a batch between devices

Full list of options, see resnet_run_loop.py

Step 5. Collect the running results

When the workload run is complete, it will display the output.

2) PyTorch based

Step 1. Required Software Stacks

1. Python 2.7
2. Anaconda 5.3.0

curl –O https://repo.anaconda.com/archive/Anaconda2-5.3.0-Linux-x86_64.sh
sh Anaconda2-5.3.0-Linux-x86_64.sh

3. Pytorch 1.0

conda install pytorch torchvision cudatoolkit=9.0 -c pytorch
(https://pytorch.org/get-started/locally/)

Step 2. Get workloads from BigDataBench

Download the Benchmark from this link:
http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz

```
$ tar –xf BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_AI_ComponentBenchmark/
$ cd PyTorch/Image_classification
```

Step 3. Prepare the input

1. Download the ImageNet dataset
2. Move validation images to labeled subfolders, you can use the following script: https://raw.githubusercontent.com/soumith/imagenetloader.torch/master/valprep.sh

Step 4. Run the workload

```
bash run_image_classify ${batchSize} ${dataDir}
```

Step 5. Collect the running results

When the workload run is complete, it will display the output.

4.3.2 Image Generation

1) TensorFlow based

Step 1. Required Software Stacks

python 2.7
tensorflow >= 1.2 (verified on 1.2 and 1.3)
tqdm

Step 2. Get workloads from BigDataBench

Download the Benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz

```
$ tar –xf BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_AI_ComponentBenchmark/
$ cd TensorFlow/Image_generation
```

Step 3. Prepare the input

```
$ ./prepareData.sh
```

Step 4. Run the workloads;

```
$ python main.py --dataset mnist --gan_type WGAN --epoch 5 --batch_size 64
```

Step 5. Collect the running results

When the workload run is complete, it will display the output.

2) PyTorch based

Step 1. Required Software Stacks

PyTorch

PyTorchvision

Step 2. Get workloads from BigDataBench

Download the Benchmark from this link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz

```
$ tar –xf BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_AI_ComponentBenchmark/
$ cd PyTorch/Image_generation
```

Step 3. Prepare the input

The dataset we use is LSUN-bedroom. http://www.yf.io/p/lsun .

You can download the dataset by:

```
$ python3 lsun/download.py -o <data_dir> -c bedroom
```

Or you can also download the lsun dataset from http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_DataSet

Step 4. Run the workload

```
$ cd WGAN
$ python main.py --mlp_G --ngf 512 --dataset lsun --dataroot <lsun-train-folder> --cuda
```

Step 5. Collect the running results

When the workload run is complete, it will display the output.

4.3.3 Text-to-Text Translation

1) TensorFlow based

Step 1. Required Software Stacks

tensorflow-gpu

tensorflow

Step 2. Get workloads from BigDataBench

Download the Benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz

```
$ tar –xf BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_AI_ComponentBenchmark/
$ cd TensorFlow/Text_to_Text
```

Step 3. Prepare the input

Download tensor2tensor from https://github.com/tensorflow/tensor2tensor. And make sure you can access to the Internet. For compatibility you need to change the io file of python.

```
vim /usr/local/lib/python3.6/dist-packages/tensorflow/python/lib/io/file_io.py
```

Change:

```
def rename(oldname, newname, overwrite=False):
def rename_v2(src, dst, overwrite=False):
```

To:

```
def rename(oldname, newname, overwrite=True):
def rename_v2(src, dst, overwrite=True):
```

Step 4. Run the workloads;

```
$./run.sh
```

Step 5. Collect the running results

When the workload run is complete, it will display the output.

2) PyTorch based

Step 1. Required Software Stacks

PyTorch 1.0.1

Step 2. Get workloads from BigDataBench

Download the Benchmark from this link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz

```
$ tar –xf BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_AI_ComponentBenchmark/
$ cd PyTorch/Text_to_Text
```

Step 3. Prepare the input

```
$ sh download.sh
```

Or you can also find the dataset from:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_DataSet

Step 4. Run the workload

```
$ sh run.sh
```

Step 5. Collect the running results

When the workload run is complete, it will display the output.

[Info] Finished.

4.3.4 Image to Text

1) TensorFlow based

Step 1. Required Software Stacks

Bazel
Natural Language Toolkit (NLTK)
Unzip
Numpy
Tensorflow 1.0 or greater

Step 2. Get workloads from BigDataBench

Download the Benchmark from the link:
http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz

```
$ tar –xf BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_AI_ComponentBenchmark/
$ cd TensorFlow/Image_to_Text
```

Step 3. Prepare the input

The dataset we use is COCO 2014. http://cocodataset.org/#download .
You can download the dataset via COCO webpage, or http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_DataSet.
After downloading the dataset, please execute the following command.

```
$ IM2TXT_HOME=/path/to/your/coco2014-dataset
$ # Directory containing preprocessed MSCOCO data.
$ MSCOCO_DIR="${IM2TXT_HOME}/im2txt/data/mscoco"
$ # Inception v3 checkpoint file.
$  INCEPTION_CHECKPOINT="${IM2TXT_HOME}/im2txt/data/inception_v3.ckpt"
$ # Directory to save the model.
$ MODEL_DIR="${IM2TXT_HOME}/im2txt/model"
$ # Build the model.
$ cd research/im2txt
$ bazel build -c opt //im2txt/..
```

Step 4. Run the workloads;

```
$ bazel-bin/im2txt/train \
 --input_file_pattern="${MSCOCO_DIR}/train-?????-of-00256" \
 --inception_checkpoint_file="${INCEPTION_CHECKPOINT}" \
 --train_dir="${MODEL_DIR}/train" \
 --train_inception=false \
 --number_of_steps=1000000
```

Step 5. Collect the running results

When the workload run is complete, it will display the output.

2) PyTorch based

Step 1. Required Software Stacks

torch

torchvision
matplotlib
nltk
numpy
Pillow
argparse
Cython
Scipy

```
$ pip install softwareName
```

Step 2. Get workloads from BigDataBench

Download the Benchmark from this link:
http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz

```
$ tar –xf BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_AI_ComponentBenchmark/
$ cd PyTorch/Image_to_Text
```

Step 3. Prepare the input

This can be done by running `$ ./prepareData.sh` or following the steps bellow:

Download the dataset from BigDataBench or website

1. Download from BigDataBench at the folder of ‘DataSet/coco2014’. Rename ‘coco2014’ as ‘data’ and then put ‘data’ in the folder of ‘Image_to_Text’.
2. Download from the website by running:

```
$ ./download.sh
```

Preprocessing

```
$ python build_vocab.py
$ python resize.py
```

Step 4. Run the workload

This can be done by running `$ ./run_imageTotext.sh` or following the steps bellow:

Train the model

```
$ python train.py
```

Test the model

```
$ python sample.py --image='png/example.png'
```

Step 5. Collect the running results

When training the model, it will display the output:

```
Epoch [0/1], Step [0/3236], Loss: 9.2094, Perplexity: 9990.5262
Epoch [0/1], Step [10/3236], Loss: 5.8074, Perplexity: 332.7434
…
```

At each ‘--save_step’, it will save the training model in the folder ‘./models’ with the name of ‘encoder-{epoch}-{step}.ckpt’ and ‘decoder-{epoch}-{step}.ckpt’. The default ‘--num_epochs’ is 5, ‘--save_step’ is 1000.

Test the model, the output is something like the following sentence.

```
<start> a man is sitting on a tennis court . <end>
```

The default training model used is ‘encoder-2-1000.ckpt’ and ‘decoder-2-1000.ckpt’, which can be changed by ‘--encoder_path’ and ‘--encoder_path’.

4.3.5 Image to Image

1) TensorFlow based

Step 1. Required Software Stacks

Pyton3
Tensorflow1.2
click (pip install click)
unzip

Step 2. Get workloads from BigDataBench

Download the Benchmark from the link:
http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz

```
$ tar –xf BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_AI_ComponentBenchmark/
$ cd TensorFlow/Image_to_Image/CycleGAN
```

Step 3. Prepare the input

```
$ ./download_datasets.sh cityscapes
```

Step 4. Run the workloads;

Add export LC_ALL=C.UTF-8 export LANG=C.UTF-8 to /etc/profile

```
$./run.sh
```

Step 5. Collect the running results

When the workload run is complete, it will display the output.

2) PyTorch based

Step 1. Required Software Stacks

PyTorch
PyTorchvision
PyDominate
PyVisdom

Step 2. Get workloads from BigDataBench

Download the Benchmark from this link:
http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz

```
$ tar –xf BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_AI_ComponentBenchmark/
$ cd PyTorch/Image_to_Image
```

Step 3. Prepare the input

The dataset we use is cityscapes.
You can download the dataset by:

```
$ bash ./datasets/download_cyclegan_dataset.sh cityscapes
```

Or you can also download the cityscapes dataset from http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_DataSet

Step 4. Run the workload

```
$ python train.py --dataroot ./datasets/ cityscapes --name cityscapes_cyclegan --model cycle_gan
```

Step 5. Collect the running results

When the workload run is complete, it will display the output.

4.3.6 Speech to Text

1) TensorFlow based

Step 1. Required Software Stacks

Python 2/3

Tensorflow>=1.1

```
$ pip/pip3 install -r requirements.txt
```

Step 2. Get workloads from BigDataBench

Download the Benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz

```
$ tar –xf BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_AI_ComponentBenchmark/
$ cd TensorFlow/Speech_to_Text
```

Step 3. Prepare the input

```
$ python data/download.py
```

Arguments:

--data_dir: Directory where to download and save the preprocessed data. By default, it is /tmp/librispeech_data.

Use the --help or -h flag to get a full list of possible arguments.

Step 4. Run the workloads;

```
$python deep_speech.py
```

Arguments:

--model_dir: Directory to save model training checkpoints. By default, it is /tmp/deep_speech_model/.

--train_data_dir: Directory of the training dataset.

--eval_data_dir: Directory of the evaluation dataset.

--num_gpus: Number of GPUs to use (specify -1 if you want to use all available GPUs).

There are other arguments about DeepSpeech2 model and training/evaluation process. Use the --help or -h flag to get a full list of possible arguments with detailed descriptions.

Step 5. Collect the running results

A shell script run_deep_speech.sh is provided to run the whole pipeline with default parameters. Issue the following command to run the benchmark:

```
sh run_deep_speech.sh
```

Note by default, the training dataset in the benchmark include train-clean-100, train-clean-360 and train-other-500, and the evaluation dataset include dev-clean and dev-other.

When the workload run is complete, it will display the output.

2) PyTorch based

Step 1. Required Software Stacks

PyTorch 1.0.1, Torchaudio, apex, warp-ctc bindings, flac, sox, tqdm, librosa, levenshtein.

Cuda 10.0+

Since the torchaudio has high compatibility requirements, we suggest using conda to create a new environment and install the speech_to_text workload. Otherwise, “import torchaudio” would report segmentation fault (core dumped). The installation processes are as follows:

i) create a new environment named imageText, note that you can change the name.

```
$ conda create –n imageText python
```

ii) activate the new environment

```
$ source activate imageText
```

iii) install PyTorch in the new environment

```
$ conda install pytorch torchvision -c pytorch
```

iv) install torchaudio

```
$ git clone https://github.com/pytorch/audio.git
$ cd audio && python setup.py install
```

v) install apex

```
$ git clone --recursive https://github.com/NVIDIA/apex.git
$ cd apex && pip install .
```

vi) install warp-ctc binding

```
$ git clone https://github.com/SeanNaren/warp-ctc.git
$ cd warp-ctc
$ mkdir build
$ cd build
$ cmake ..
$ make
```

Note that the conda environment may install the gcc 6+ version, while warp-ctc doesn’t support gcc 6+, so you need to edit the CMakeLists.txt file to use old gcc version. Insert the following two lines in CMakeLists.txt (you need to change the path of old gcc version according to your environment) and then repeat the upper commands.

```
SET(CMAKE_C_COMPILER "/usr/bin/gcc4.8")
SET(CMAKE_CXX_COMPILER "/usr/bin/g++4.8")
```

vii) install pytorch_binding

```
$ cd warp-ctc/pytorch_binding
$ python setup.py install
```

viii) install flac

```
$ wget https://ftp.osuosl.org/pub/xiph/releases/flac/flac-1.2.1.tar.gz
$ tar –xf flac-1.2.1.tar.gz
$ cd flac-1.2.1
$ ./configure && make && make install
```

Note that if you encounter the error “main.cpp:75:27: error: 'memcmp' was not declared in this scope”, you need to insert “#include <string.h> ” in the file “examples/cpp/encode/file/main.cpp”.

ix) install sox

Download sox-14.4.2.tar.gz from

https://sourceforge.net/projects/sox/files/sox/14.4.2/sox-14.4.2.tar.gz/download

```
$ ./configure --with-lame --with-flac --with-libvorbis
$ make -s
$ make install
```

x) install tqdm, librosa, and levenshtein

```
$ pip install tqdm
$ pip install librosa
$ pip install python-levenshtein
```

Step 2. Get workloads from BigDataBench

Download the Benchmark from this link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz

```
$ tar –xf BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_AI_ComponentBenchmark/
$ cd PyTorch/Speech_to_Text
```

Step 3. Prepare the input

The workload use LibriSpeech dataset. Preprocess the dataset:

```
$ cd deepspeech.pytorch/data
$ mkdir LibriSpeech_dataset
$ mkdir LibriSpeech_dataset/test_clean
$ mkdir LibriSpeech_dataset/test_other
$ mkdir LibriSpeech_dataset/train
$ mkdir LibriSpeech_dataset/val
$ python librispeech.py
```

you can use the parameter --files-to-use to specify the dataset.

The command will generate four files under the data directory:

libri_test_clean_manifest.csv,

libri_test_other_manifest.csv,

libri_train_manifest.csv,

libri_val_manifest.csv

Step 4. Run the workload

Training use CPU:

```
$ python train.py --train-manifest data/libri_train_manifest.csv --val-manifest data/libri_val_manifest.csv
```

Training use GPU:

```
$ python train.py --train-manifest data/libri_train_manifest.csv --val-manifest data/libri_val_manifest.csv –cuda
```

Testing use CPU:

```
$ python test.py --model-path models/deepspeech_final.pth --test-manifest data/libri_test_clean_manifest.csv
```

Testing use GPU:

```
$ python test.py --model-path models/deepspeech_final.pth --test-manifest data/libri_test_clean_manifest.csv --cuda
```

Step 5. Collect the running results

When the workload run is complete, it will display the output.

4.3.7 Face Embedding

1) TensorFlow based

Step 1. Required Software Stacks

Tensorflow
Scipy
Scikit-learn
Opencv-python
H5py
Matplotlib
Pillow
Requests
Psutil

Step 2. Get workloads from BigDataBench

Download the Benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz

```
$ tar –xf BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_AI_ComponentBenchmark/
$ cd TensorFlow/Face_embedding
```

Step 3. Prepare the input

The dataset we use is VGGFace2. http://zeus.robots.ox.ac.uk/vgg_face2/login/ .

You can download dataset from VGGFace2 webpage, or you can also download the cityscapes dataset from:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_DataSet .

After downloading the dataset, you also need to perform the image alignment, which might take several hours.

```
$ ../scripts/face-align-VGGface2.sh
```

Step 4. Run the workloads;

```
$ ../scripts/cls_training_triplet_webface.sh
```

Step 5. Collect the running results

When the workload run is complete, it will display the output.

2) PyTorch based

Step 1. Required Software Stacks

Pytorch 1.0.1

Step 2. Get workloads from BigDataBench

Download the Benchmark from this link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz

```
$ tar –xf BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_AI_ComponentBenchmark/
$ cd PyTorch/Face_embedding/facenet
```

Step 3. Prepare the input

Rewrite `datasets/write_csv_for_making_dataset.py`， you need to change `which_dataset` and `root_dir`。

Step 4. Run the workload

```
$ python train.py
```

Step 5. Collect the running results

When the workload run is complete, it will display the output.

4.3.8 Object Detection

1) TensorFlow based

Step 1. Required Software Stacks

Python 3.3+;
OpenCV;
TensorFlow>1.6;

Step 2. Get workloads from BigDataBench

Download the Benchmark from the link:
http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz

```
$ tar –xf BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_AI_ComponentBenchmark/
$ cd TensorFlow/Object_detection
```

Step 3. Prepare the input

To prepare the data:
./prepareData.sh

Step 4. Run the workloads;

i) To train on a single machine:
./run_objectDetect.sh
ii) To run distributed training:
Set TRAINER=horovod in the config.py file
./run_objectDetect.sh

Step 5. Collect the running results

When the workload run is complete, it will display the output.

2) PyTorch based

Step 1. Required Software Stacks

PyTorch
CyThon
Cffi

Opencv-python
Scipy
Msgpack
Easydict
Matplotlib
Pyyarml
TensorboardX

Step 2. Get workloads from BigDataBench

Download the Benchmark from this link:
http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz

```
$ tar –xf BigDataBench_V5.0_AI_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_AI_ComponentBenchmark/
$ cd PyTorch/Object_detection
```

Step 3. Prepare the input

The dataset we use is COCO 2014. http://cocodataset.org/#download .
You can download the dataset via COCO webpage, or http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_DataSet.
After downloading the dataset, please execute the following command.

```
$ # set your own coco dataset path
$ COCO_PATH=/your/path/to/coco2014
$ mkdir -p data data/pretrained_model
$ set -x
$ if [[ ! -d data/coco ]]; then
$ cd data
$ git clone https://github.com/pdollar/coco.git && cd coco/PythonAPI
$ make -j32 && cd ../../
$ cd ../
$ fi
$ if [[ ! -f data/coco/annotations || ! -h data/coco/annotations ]]; then
$    ln -sv $COCO_PATH/annotations data/coco/annotations
$ fi
$ if [[ ! -f data/coco/images  || ! -h data/coco/images ]]; then
$    ln -sv $COCO_PATH data/coco/images
$ fi
```

Step 4. Run the workload

```
$ ./scripts/train.sh
```

Step 5. Collect the running results

When the workload run is complete, it will display the output.

4.3.9 Recommendation - CF

1) Hadoop based

Step 1. Required Software Stacks

Java JDK

Step 2. Get workloads from BigDataBench

Download the Benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz

Step 3. Prepare the input

```
$ tar –xf BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_BigData_ComponentBenchmark/Hadoop/CF
$ ./genData-cf.sh <size>
```

The parameter “size” means the input data size (GB).

Step 4. Run the workloads;

```
$ ./run-cf.sh <size> <numFeatures> <numIterations> <lambda>
```

#size: the input data size, GB

#numFeatures: the number of features

#numIterations: the number of features

#lambda: regularization parameter

Step 5. Collect the running results

When the workload run complete, it will display the running information and generate output file: /hadoop/cf/cf-out

2) Spark based

Step 1. Required Software Stacks

CentOS

Step 2. Get workloads from BigDataBench

Download the Benchmark from this link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz

Step 3. Prepare the input

```
$ tar –xf BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_BigData_ComponentBenchmark/Spark/CF
$ ./genData-cf.sh <size>
```

The parameter “size” means the input data size (GB).

Step 4. Run the workload

```
$ ./runSpark-cf.sh <ratings_file> <rank> <iterations>
```

parameters:

<ratings_file>: path of input data file

<rank>: number of features to train the model

<iterations>: number of iterations to run the algorithm

Step 5. Collect the running results

When the workload run is complete, it will display the running information.

4.3.10 PageRank

1) Hadoop based

Step 1. Required Software Stacks

Hadoop

BGDS

Step 2. Get workloads from BigDataBench

Download the benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz

Decompress the Hadoop package.

```
$ tar -zxvf BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz
```

Prepare:

```
$ cd BigDataBench_V5.0_BigData_ComponentBenchmark/Hadoop
$ ./prepar.sh
```

Step 3. Prepare the input

```
$ cd PageRank/
$./genData-pagerank.sh <log_vertex>
```

Parameter “log_vertex” indicates that the vertex of the generated graph is 2^$I.

The generated data is on HDFS under /hadoop/pagerank directory.

Step 4. Run the workload

```
$ ./run-PageRank.sh <log_vertex>
```

Parameter “log_vertex” indicates that the vertex of the generated graph is 2^$I.

Step 5. Collect the running results

The output of the workload will be put in hdfs with location: /hadoop/pagerank/output.

2) Spark based

Step 1. Required Software Stacks

Spark

BGDS

Step 2. Get workloads from BigDataBench

Download the benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz

Decompress the package.

```
$ tar -zxvf BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz
```

Step 3. Prepare the input

```
$ cd BigDataBench_V5.0_BigData_ComponentBenchmark/Spark
$ cd Pagerank
$ ./genData-pagerank.sh <log_vertex>
```

Parameter “log_vertex” indicates that the vertex of the generated graph is 2^$I.

The generated data is on HDFS under /spark/pagerank directory.

Step 4. Run the workload

```
$ ./runSpark-PageRank.sh <log_vertex>
```

Parameter “log_vertex” indicates that the vertex of the generated graph is 2^$I.

Step 5. Collect the running results

The output of the workload will be put in hdfs with location: /spark/pagerank/output.

3) Flink based

Step 1. Required Software Stacks

Flink

BGDS

Step 2. Get workloads from BigDataBench

Download the benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz

Decompress the Hadoop package.

```
$ tar -zxvf BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz
```

Prepare:

```
$ cd BigDataBench_V5.0_BigData_ComponentBenchmark/
$ ./prepar.sh
```

Step 3. Prepare the input

```
$ cd Flink/Pagerank/
$./genData_PageRank.sh
```

You need to input the iteration $I of GenGraph, and it indicates that the vertex of the generated graph is 2^$I.

The generated data is on HDFS under /data-PageRank/Google_genGraph_$I.txt directory.

Step 4. Run the workload

```
$ ./run_Pagerank.sh
```

You need to input the iteration $I of GenGraph, and it indicates that the vertex of the generated graph is 2^$I.

Step 5. Collect the running results

The output of the workload will be put in hdfs with location: /flink-pagerank-result.

4) MPI based

MPI_Pagerank is a parallel implementation of pagerank algorithm.

Step 1. Required software stacks

MPICH2

Cmake: Cmake 2.8.12.2 is prefered Boost1.43.0

When you install the boost packet, make sure that the mpi packet has been installed.

```
$sh bootstrap.sh
$./bjam
```

Building parallel-bgl-0.7.0:

```
$ cd BigDataBench_V5.0_BigData_ComponentBenchmark/MPI
```

```
$ cd Pagerank/parallel-bgl -0.7.0
$ cmake ./
$ cd parallel-bgl-0.7.0/libs/graph_parallel/test
$ make distributed_page_rank_test
```

Step 2. Get workload MPI_Pagerank from BigDataBench

Download the benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz

Step 3. Prepare the input

The data set used by MPI_Pagerank is generated by big data generation tool (BDGS).

To generate data:

i) Unpack the downloaded tar file

```
$ tar –xf BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_BigData_ComponentBenchmark/MPI/MPI_Pagerank
```

ii) Generate data

```
$ ./genData_PageRank.sh
```

Input the Iterations of GenGragh, after this step, it will generate data-PageRank under the Pagerank directory.

Step 4. Run the workload

i) Unpack the downloaded tar file

```
$ tar –xf BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_BigData_ComponentBenchmark/MPI/MPI_Pagerank
```

ii) Install Pagerank

We provide a Compiled executable program named run_PageRank under the Pagerank directory.

iii) Run the workload

Run MPI Pagerank, command is:

```
$mpirun -f machine_file -n PROCESS_NUM ./run_PageRank InputGraph-file num_ofVertex num_ofEdges iterations
```

Step 5. Collect the running results

When the workload run is complete, it will display the running information, such as:

INFO: Starting PageRank.
INFO: Params:
InputGraphfile=data-PageRank/Google_genGraph_10.txt,
num_ofVertex=1024, num_ofEdges=2147, iterations=5
256 = 0.813656

Note that if you want to collect the performance data on system or architecture level, you should run corresponding scripts in the background to collect data.

Note:

The two parameters (num_ofVertex, num_ofEdges) in running command line can be found in standard output when you generate data, such as:

[root Pagerank]# ./genData_PageRank.sh
Generate PageRank data

Please Enter The Iterations of GenGragh: 5
WORK_DIR=/BigDataBench_V5.0_BigData_ComponentBenchmark/MPI/Pagerank
data will be generated under Pagerank/data-PageRank
sh: gnuplot: command not found
Kronecker graphs. build: 10:42:53, Apr 21 2014. Time: 00:54:50 [Mar 2014]
==
Output graph file name (-o:)= Pagerank/data-PageRank/Google_genGraph_5.txt
Matrix (in Maltab notation) (-m:)=0.8305 0.5573; 0.4638 0.3021 Iterations of Kronecker product (-i:)=5
Random seed (0 - time seed) (-s:)=0
*** Seed matrix:
0.8305 0.5573
0.4638 0.3021 (sum:2.1537)
*** Kronecker:
FastKronecker: 32 nodes, 46 edges, Directed...
run time: 0.00s (00:54:50)

4.3.11 Index

1) Hadoop based

Step 1. Required Software Stacks

Hadoop
BGDS

Step 2. Get workloads from BigDataBench

Download the benchmark from the link:
http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz

Decompress the package.

```
$ tar -zxvf BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz
```

Prepare:

```
$ cd BigDataBench_V5.0_BigData_ComponentBenchmark
$ ./prepar.sh
```

Step 3. Prepare the input

When prepare the input file linux.words and words, you should put them in dirctory /usr/share/dict.

```
$ cd Hadoop/Index/bin
$ ./genData_Index.sh
```

Then you will be asked how many data you like to generate:
Preparing MicroBenchmarks data dir
WORK_DIR=/BigDataBench_V5.0_BigData_ComponentBenchmark/Hadoop/Index data will be put in Index/data-Index print data size GB : (enter a number here)

Step 4. Run the workload

```
$ cd Hadoop/Index/bin
```

$ ./run_Index.sh

Step 5. Collect the running results

The output of the workload will be put in local directory: result and the ourput is redirected to file: Index.out

4.3.12 BFS

1) MPI based

MPI_BFS is an MPI-based implementation of breadth-first search.

Step 1. Required software stacks

MPICH2

Step 2. Get workload MPI_BFS from BigDataBench

Download the benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz

Step 3. Prepare the input

The data set used by BFS is generated by the program itself.

Step 4. Run the workload

i) Unpack the downloaded tar file

$ tar -zxvf BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz

$ cd BigDataBench_V5.0_BigData_ComponentBenchmark/MPI/

$ cd BFS-MPI/graph500

ii) Build the MPI executables

$ vim make.inc

set the BUILD_MPI = Yes

Change the last line MPICC = XXX -IXXX -LXXX, according to your own MPI installation directory.

In our example, it should be change to MPICC = /home/mpich2-ins/bin/mpicc -I/home/mpich2-ins/include -L/home/mpich2-ins/lib

Save and exit vim

Using the command to build:

$ make

After this step, there will be two executables files named graph500_mpi_simple and graph500_mpi_one_sided under directory BFS/graph500/mpi.

iii) Run the workload

$cd BFS-MPI/graph500/mpi

$mpirun -f machine_file -n PROCESS_NUM ./graph500_mpi_simple SCALE edgefactor

Note: as previously mentioned (step 4.3), the machine_file contains the node information;

PROCESS_NUM specifies the number of processes;

SCALE and edgefactor are two parameters required by graph500_mpi_simple;

SCALE should be an integer value and specifies the number of vertices to be 2SCALE. This parameter must be provided;

edgefactor is a double value with a default value of 16. It specifies the number of edges to be (edgefactor 2SCALE). This parameter can be omitted.

For example:

```
$mpirun -f machine_file -n 12 ./graph500_mpi_simple 20 15
$mpirun -f machine_file -n 12 ./graph500_mpi_simple 20
```

Step 5. Collect the running results

When the workload run is complete, it will display the running information, such as:
SCALE: 20
edgefactor: 15
NBFS: 64
graph_generation: 6.62665 s
num_mpi_processes: 4
construction_time: 54.5597 s
min_time: 0.287835 s
……
Steps=: 1470480

Note that if you want to collect the performance data on system or architecture level, you should run corresponding scripts in the background to collect data.

4.3.13 K-means

1) Hadoop based

Step 1. Required Software Stacks

Hadoop
BGDS

Step 2. Get workloads from BigDataBench

Download the benchmark from the link:
http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz

Decompress the Hadoop package.

```
$ tar -zxvf BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_BigData_ComponentBenchmark/Hadoop
```

Step 3. Prepare the input

```
$ cd Kmeans/
$./genData-kmeans.sh <log_vertex>
```

Parameter “log_vertex” indicates that the vertex of the generated graph is 2^$I.
The generated data is on HDFS under /user/root/testdata directory.

Step 4. Run the workload

```
$ ./run-Kmeans.sh <t1> <t2> <cd> <x>
```

Parameter:
t1: T1 threshold value (0-1), such as 0.4
t2: T2 threshold value (0-1), such as 0.1
cd: The convergence delta value (0-1), such as 0.1
x: The max iteration number

Step 5. Collect the running results

The output of the workload will be put in hdfs with location: /user/root/output.

2) Spark based

Step 1. Required Software Stacks

Spark

BGDS

Step 2. Get workloads from BigDataBench

Download the benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz

Decompress the Hadoop package.

```
$ tar -zxvf BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_BigData_ComponentBenchmark/Spark
```

Step 3. Prepare the input

```
$ cd Kmeans/
$./genData-kmeans.sh <size>
```

Parameter "size" indicates the input data size (GB).

The generated data is on HDFS under /spark/kmeans/ directory.

Step 4. Run the workload

```
$ ./runSpark-Kmeans.sh <size> <centerNum> <iterNum>
```

Parameter:

\# size: the input data size (GB)

\# centerNum: the number of center points.

\# iterNum: the max iteration number

Step 5. Collect the running results

The output of the workload will be put in hdfs.

3) Flink based

Step 1. Required Software Stacks

Flink

BGDS

Step 2. Get workloads from BigDataBench

Download the benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz

Decompress the package.

```
$ tar -zxvf BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_BigData_ComponentBenchmark/Flink
```

Step 3. Prepare the input

```
$ cd Kmeans/
$./genData_Kmeans.sh
```

Then you need to input the data size (GB) you want to generate. The data will be put under /Flink-Kmeans directory on HDFS.

Step 4. Run the workload

```
$ ./run_Kmeans.sh
```

You will need to input the number of centers and the number of max iterations.

Step 5. Collect the running results

The output of the workload will be put in hdfs.

4) MPI based

Step 1. Required software stacks

MPICH2

Step 2. Get workload MPI_Kmeans from BigDataBench

Download the benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz

Step 3. Prepare the input

The data set used by MPI_Kmeans is generated by a generating script.

To generate data:

i) Unpack the downloaded tar file

```
$ tar -zxvf BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_BigData_ComponentBenchmark/
$ cd MPI/Simple_Kmeans
```

ii) Generate data

```
$ sh genData_Kmeans.sh
```

Input the data size you want to generate with the units of GB, such as 10 if you want to generat 10 GB data. After this step, it will generate data-Kmeans file under directory of Simple_Kmeans.

Step 4. Run the workload

```
$cd MPI/Simple_Kmeans
```

Install MPI_Kmeans

```
$make
```

After this step, there will be an executable files named mpi_main under the current directory.

Run MPI_Kmeans command:

```
$mpirun -f machine_file -n PROCESS_NUM ./mpi_main -i input_file -n cluster_number -o
```

Note: the input_file specifies the name of the input file, such as data-Kmeans;

The cluster_number specifies the number of clusters, such as 5;

-o parameter means output timing results

The coordinates of all cluster centers are writed to file "data-Kmeans.cluster_centres", and the membership of all data objects are writed to file "data-Kmeans.membership".

5. Collect the running results

When the workload run is complete, it will display the running information, such as:

mpi_kmeans is 3.461451 Seconds

Writing coordinates of K=5 cluster centers to file "data-Kmeans.cluster_centres"

Writing membership of N=23000000 data objects to file "data-Kmeans.membership"

Performing **** Simple Kmeans (MPI) ****

……

Computation timing = 3.9639 sec
FPCount=3359518,IntCount=3622512465

Note that if you want to collect the performance data on system or architecture level, you should run corresponding scripts in the background to collect data.

Note:

For more information about parameters of mpi_main: Usage: ./mpi_main [switches] -i filename -n num_clusters -i filename : file containing data to be clustered -b : input file is in binary format (default no)

-r : output file in binary format (default no)
-n num_clusters: number of clusters (K must > 1)
-t threshold : threshold value (default 0.0010)
-o : output timing results (default no)
-d : enable debug mode

4.3.14 NaiveBayes

The Naive Bayes is a simple probabilistic classifier, which applies the Bayes' theorem with strong (naive) independency assumptions.

1) Hadoop based

Step 1. Required Software Stacks

Hadoop
BDGS

Step 2. Get workloads from BigDataBench

Download the benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz

Decompress the Hadoop package.

```
$ tar -zxvf BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz
```

Step 3. Prepare the input

```
$ cd BigDataBench_V5.0_BigData_ComponentBenchmark/Hadoop/Bayes
$ ./genData-bayes.sh <size>
```

The parameter "size" means the input data size (GB).

The data will be generated in /hadoop/Bayes/ on HDFS.

Step 4. Run the workload

Use the apache-mahout-0.10.2-compile under the Hadoop directory and set $MAHOUT_HOME in ~/.bashrc file.

```
$ ./run-bayes.sh
```

Step 5. Collect the running results

The output will be printed on the screen.

2) Spark based

Step 1. Required Software Stacks

Spark
BGDS

Step 2. Get workloads from BigDataBench

Download the benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz

```
$ tar -zxvf BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz
```

Step 3. Prepare the input

```
$ cd BigDataBench_V5.0_BigData_ComponentBenchmark/Spark/Bayes
$ ./genData-bayes.sh <size>
```

The parameter "size" means the input data size (GB).

The data will be generated in /spark/Bayes/ on HDFS.

Step 4. Run the workload

```
$ ./runSpark-bayes.sh <size>
```

The parameter "size" means the input data size (GB).

Step 5. Collect the running results

The output of the workload will be put in hdfs with location: /spark/Bayes/output.

3) Flink based

Step 1. Required Software Stacks

Flink

BDGS

Step 2. Get workloads from BigDataBench

Download the benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz

Decompress the Hadoop package.

```
$ tar -zxvf BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz
```

Step 3. Prepare the input

```
$ cd BigDataBench_V5.0_BigData_ComponentBenchmark/Flink/naivebayes
$ ./genData_naivebayes.sh
```

You need to input the data size (GB) you want to generate.

The data will be generated in /Bayesclassifier/testdata on HDFS.

Step 4. Run the workload

```
$ ./run_naivebayes.sh
```

Step 5. Collect the running results

The output will be put on /flink-Bayes-result directory.

4) MPI based

MPI_NaiveBayes is a mpi-based implementation of naive bayes algorithm.

Step 1. Required software stacks

MPICH2

Step 2. Get workload MPI_NaiveBayes from BigDataBench

Download the benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz

```
$ tar -zxvf BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz
```

Step 3. Prepare the input

$ cd BigDataBench_V5.0_BigData_ComponentBenchmark/MPI/MPI_naviebayes
$ ./genData_naivebayes.sh

Then you will be asked how many data you would like to generate:

Preparing naivebayes-naivebayes data dir

WORK_DIR=Naviebayes will be generated in Naviebayes/data-naivebayes

Preparing naivebayes-naivebayes data dir

print data size GB : (enter a number here)

Step 4. Run the workload

Install MPI_NaiveBayes

We provide two executable files (MPI_NB_train, MPI_NB_predict) under directory MPI/Naivebayes.

Run the workload

To train bayes model, the command is:

$mpirun -f machine_file -n PROCESS_NUM ./MPI_NB_train -i input_file -o train_model

To run naive bayes, the command is:

$mpirun -f machine_file -n PROCESS_NUM ./MPI_NB_predict -m train_model -i input_file -o output_file

5. Collect the running results

Note that if you want to collect the performance data on system or architecture level, you should run corresponding scripts in the background to collect data.

4.3.15 LDA

1) Spark based

Step 1. Required Software Stacks

Spark
BDGS

Step 2. Get workloads from BigDataBench

Download the benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz

Decompress the Hadoop package.

$ tar -zxvf BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz

Step 3. Prepare the input

$ cd BigDataBench_V5.0_BigData_ComponentBenchmark/Spark/LDA
$ ./genData-lda.sh <size>

The parameter “size” means the input data size (GB).

The data will be generated in /spark/lda/wiki-$a"G" on HDFS.

After the generation, dictionary file and corpus file will be generated on HDFS: /spark/lda/dictionary /spark/lda/corpus

Step 4. Run the workload

$ ./runSpark-lda.sh

Step 5. Collect the running results

The output will be printed on the screen.

2) MPI based

Step 1. Required Software Stacks

MPICH2
BDGS

Step 2. Get workloads from BigDataBench

Download the benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz

Decompress the Hadoop package.

```
$ tar -zxvf BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz
```

Step 3. Prepare the input

```
$ cd BigDataBench_V5.0_BigData_ComponentBenchmark/MPI/mpiLDA
$ ./genData-mpiLDA.sh <size>
```

The parameter "size" means the input data size (GB).

The data will be generated in ldaData-{size}GB.

Step 4. Run the workload

```
$ ./run-mpiLDA.sh <size>
```

The parameter "size" means the input data size (GB), which is the same with the generating command.

Step 5. Collect the running results

The output will be printed on the screen.

4.3.16 SIFT

1) Hadoop based

Step 1. Required Software Stacks

Hadoop

Step 2. Get workloads from BigDataBench

Download the benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz

Decompress the Hadoop package.

```
$ tar -zxvf BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz
```

Step 3. Prepare the input

```
$ cd BigDataBench_V5.0_BigData_ComponentBenchmark/Hadoop/SIFT
```

SIFT workload uses ImageNet dataset, and the dataset is put under Hadoop/SIFT/hadoop-SIFT/data directory.

Step 4. Run the workload

```
$ ./run-sift.sh <imgsize>
```

The parameter "imgsize" indicates the input image size (GB).

Step 5. Collect the running results

The output will be printed on the screen.

2) MPI based

MPI SIFT workload is an adaptation of David Lowes source code, which detects and describes local features in input images. We modified it to a data parallel version using MPI.

Step 1. Required software stacks

MPICH2

OpenCV package http://sourceforge.net/projects/opencvlibrary/

GDK/GTK+2 http://www.gtk.org/

Step 2. Get workload SIFT from BigDataBench

Download the benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz

```
$ tar -zxvf BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz
```

Step 3. Prepare the input

The data set used by SIFT is unstructured images from ImageNet. To get 1 GB image data: http://prof.ict.ac.cn/bdb_uploads/Media-data/ImageNet_1G.tar.gz

To get 10 GB image data: http://prof.ict.ac.cn/bdb_uploads/Media-data/ImageNet_10G.tar.gz

To get more image data, please visit ImageNet: http://www.image-net.org Here, we assume that you have downloaded the required image data (such as ImageNet_1G.tar.gz), and have be put under the directory of textbf/data/ImageNet_1G.

Step 4. Run the workload

Unpack the downloaded tar file

```
$ tar -zxvf BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_BigData_ComponentBenchmark/MPI/mpiSIFT
```

Build the MPI executables

```
$make
```

After this step, there will be an executable file named siftfeat_mpi under directory SIFT/bin.

Run the workload

Using getPath script under directory Multimedia-MPI to generate the path of image files:

```
$ sh ../../../getPath /data/ImageNet_1G imagenet_1G
```

Note that the current directory is under SIFT/bin, then the getPath file is under ../../../getPath

After this step, there will be a path file named imagenet_1G.path under your current directory (SIFT/bin in our example).

```
$mpirun -f machine_file -n PROCESS_NUM ./siftfeat_mpi PATH_FILE
```

Note: as previously mentioned, the machine_file contains the node information; PROCESS_NUM specifies the number of processes;

PATH_FILE specifies the path of image data generated by genPath.

Type $./siftfeat_mpi -h for more help.

In our example, the command will be:

```
$mpirun -f machine_file -n 12 ./siftfeat_mpi imagenet_1G.path
```

Step 5. Collect the running results

When the workload run is complete, it will display the running information, such as:

Loading file and sift begin:

Processing 7851 images, Complete!

Note that if you want to collect the performance data on system or architecture level, you should run corresponding scripts in the background to collect data.

Note

Install GDK/GTK+2: $yum install gtk+*

Install cmake: version 2.8.12.2 or higher

Install OpenCV: $cmake . $make $make install

If when you type $make to make SIFT workload of siftfeat_mpi and get error information "package opencv was not found in the pkg-config search path" after you have installed opencv package, you should add PKG_CONFIG_PATH with the directory of opencv.pc to /.bashrc file. For example, we assume that the file opencv.pc is under /usr/local/lib/pkgconfig directory, then you should add the following two sentences in file /.bashrc:

```
$ vim ~/.bashrc
        PKG_CONFIG_PATH=$PKG_CONFIG_PATH:/usr/local/lib/pkgconfig Export
        PKG_CONFIG_PATH
```

Save and exit vim

```
$ source ~/.bashrc
```

If you type $make to generate siftfeat_mpi file, and get the error information "doxygen: Command not found", you can ignore this error and it will still generate siftfeat_mpi under SIFT/bin.

If you have failed when type $make to generate siftfeat_mpi file, you need to type $make clean before your next make command.

4.3.17 DBN

1) MPI based

DBN workload is a MPI implementation of deep belief networks.

Step 1. Required software stacks

MPICH2

Step 2. Get workload DBN from BigDataBench

Download the benchmark from the link:

http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz

Step 3. Prepare the input

The data set used by DBN is MNIST (http://yann.lecun.com/exdb/mnist/). The data set is also packed in Multimedia-MPI.tar.gz, under directory Multimedia-MPI/DBN/data.

Step 4. Run the workload

Unpack the downloaded tar file

```
$ tar -zxvf BigDataBench_V5.0_BigData_ComponentBenchmark.tar.gz
$ cd BigDataBench_V5.0_BigData_ComponentBenchmark/MPI/DBN
```

Build the MPI executables

```
$ cd src
```

Using the command to build DBN:

```
$mpic++ DBN.cpp deep.o -o DBN
```

Using the command to build RBM:

```
$ mpic++ RBM.cpp deep.o -o RBM
```

Using the command to build StackedRBMS:

```
$ mpic++ StackedRBMS.cpp deep.o -o StackedRBMS
```

Using the command to build BP:

```
$ mpic++ BP.cpp deep.o -o BP
```

After this step, you will get four executables files named DBN, RBM, StackedRBMS and BP under directory DBN/src, respectively.

Run the workload:

```
$ cd Multimedia-MPI/DBN/src
```

Run DBN:

```
$ mpirun -f machine_file -n PROCESS_NUM ./DBN
```

Run RBM:

```
$ mpirun -f machine_file -n PROCESS_NUM ./RBM
```

Run StackedRBMS:

```
$ mpirun -f machine_file -n PROCESS_NUM ./StackedRBMS
```

Run BP4:

```
$ mpirun -f machine_file -n PROCESS_NUM ./BP
```

Note: as previously mentioned, the machine_file contains the node information; PROCESS_NUM specifies the number of processes.

Step 5. Collect the running results

Note that if you want to collect the performance data on system or architecture level, you should run corresponding scripts in the background to collect data.

For more information about DBN workload, please refer to: MPI/DBN/README

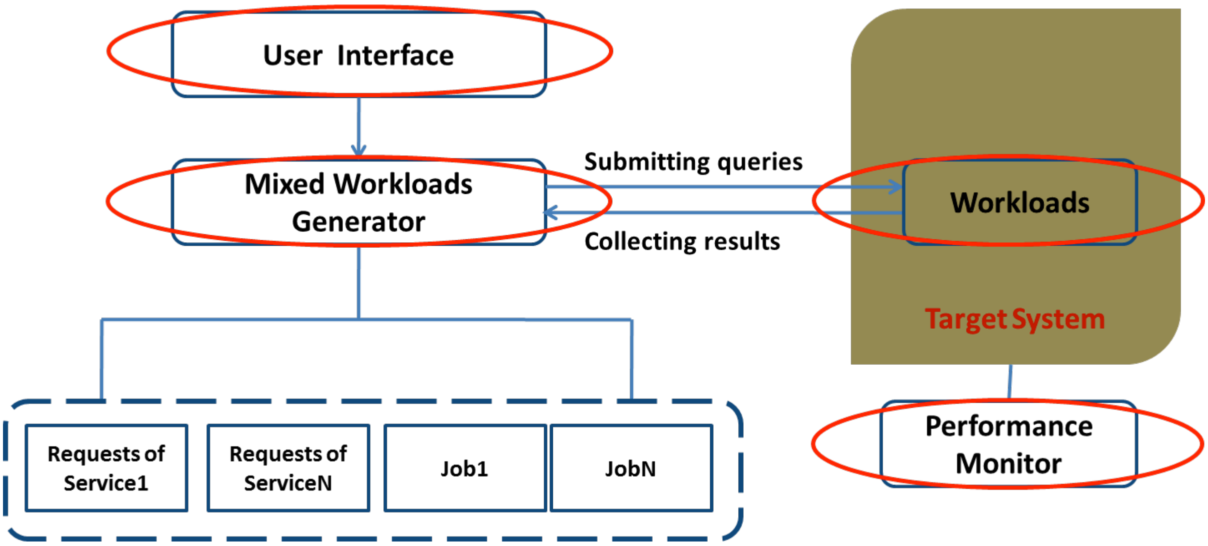
4.4 Application Benchmarks

4.4.1 DCMix

4.4.1.1 Introduction

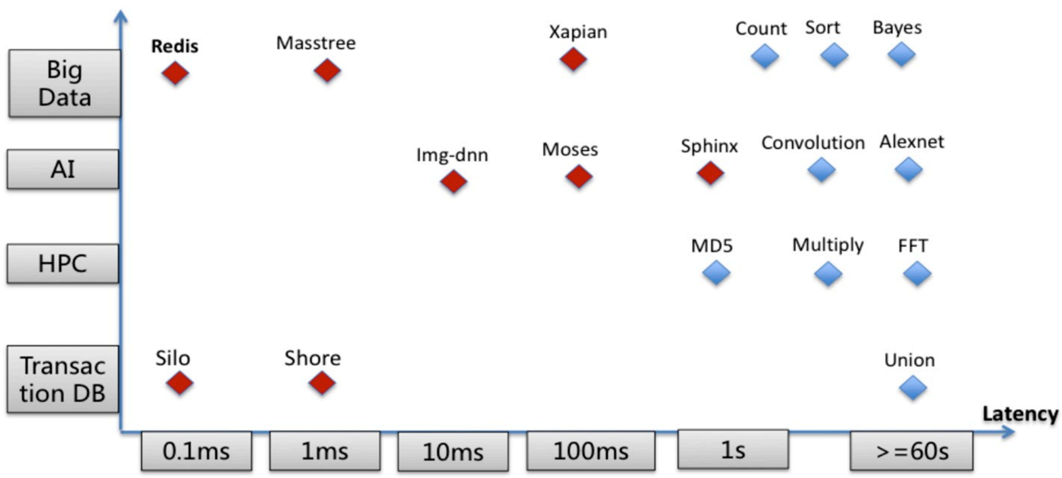
Modern datacenter computer systems are widely deployed with mixed workloads to improve system utilization and save cost. However, the throughput of latency-critical workloads is dominated by their worst-case performance-tail latency. To model this important application scenario, we propose an end-to-end application benchmark---DCMix to generate mixed workloads whose latencies range from microseconds to minutes with four mixed execution modes.

4.4.1.2 DCMix Framework



There are four main modules: Workloads, User interface, mixed workloads generator, and Performance monitor. DCMIX contains two types of workloads: online service and data analytic workloads and they are all deployed on the target system. User interface is the portal for user; users can specify their workload mix requirements, including workloads and mixture patterns. Mixed workloads generator can generate the mixed workloads through submitting queries (service requests queries and data analytics job submitting queries). Performance monitor can monitor the performance data of the target system, and the system entropy is calculated by these original monitor data.

1) Workload Overview



DCMIX contains two types of workloads: online service and data analytic workloads. These workloads have different application fields and different user experience (latency). DCMIX's application fields are big data, artificial intelligence, high-performance computing, transaction processing databases, et al. The latencies of DCMIX workloads range from microseconds to minutes.

2) Mixed Workload Generator

Mixed workloads generator can generate the mixed workloads through submitting queries (service requests queries and data analytics job submitting queries). Mixed workloads generator supports the mixture execution of serial execution and parallel execution. Serial execution means that the workload must start up after the previous workload complete. Parallel execution means that multiple workloads start up at the same time. Moreover, in the workload generator configuration file, users can set request configurations for each workload. For online-services, we provided request intensity, number of requests, number of warm-up requests, etc.; for offline-analytics, we provide path of the data set, threads number of jobs, etc.

4.4.1.3 How to use

Step 1. Required software

Python, gcc, gcc-c++, make, automake, autoconf, epel-release, libtool, libuuid,e2fsprogs, opencv, bison, swig, boost-devel, realine-devel,libdb-cxx-devel,numactl-devel,libaio-devel

Step 2. Download DCMix

You can download DCMIX via http://prof.ict.ac.cn/bdb_uploads/bdb_5/packages/DCMIX.tar.gz

Step 3. Install DCMix

1. To install tailbench workloads (i.e, online services):

```
$ cd tailbench-v0.9
$ bash ./build.sh
```

2. To install dwarf workloads (i.e, offline applications):

```
$ cd dwarf-set
$ bash ./build.sh
```

Step 4. Prepare the input data

1. To get tailbench dataset:

```
$ mkdir -p tailbench-data
$ wget -c http://tailbench.csail.mit.edu/tailbench.inputs.tgz
```

2. To generate dwarf dataset:

```
$ g++ -std=c++11 gen-data.cpp -o gen-data
$ ./gen-data
```

Step 5. Run DCMix Workload

1. To run tailbench workloads, let's take xapian as an example:

```
$ cd tailbenchv-0.9/xapian
$ ./run_xapian_server.sh
$ ./run_xapian_client.sh
```

You can set the request parameters in the above 2 script files.

2. To run dwarf workloads:

```
$ ./run_all.sh
```

4.5 Multitenancy

This tool focuses on a mix of workloads whose arrivals follow patterns hidden in real-world traces. Two type of representative data center workloads are considered:

- Long-running service workloads. These workloads offer online services such as web search engines and e-commerce sites to end users and the services usually keep running for months and years. The tenants of such workloads are service end users.

- Short-term data analytic workloads. These workloads process input data of different scales (from KB to PB) using relatively short periods (from a few seconds to several hours). Example workloads are Hadoop, Spark and Shark jobs. The tenants of such workloads are job submitters.

4.5.1 Environment setup

Step 1. Versions of software

CentOS 6.0
JKD 1.7
Python 2.7

Step 2. Hadoop cluster setup

Refer to http://hadoop.apache.org/#Getting+Started

Step 3. Environment setup of Nutch search engine

Refer to http://prof.ict.ac.cn/DCBenchmarks/Search_manual_v1.0.pdf
Search source code download: http://prof.ict.ac.cn/DCBenchmarks

Note: In Search installation, if using normal user to login, you need to set password-free logins

Step 4. Shark environment setup

Referred to https://github.com/amplab/shark/wiki/Running-Shark-on-a-Cluster

Step 5. Environment variable configuration

Configure variables at /etc/profile

```
HADOOP_HOME=/opt/hadoop-1.2.1
SEARCH_H0ME=/opt/search/search
```

Step 6. Copy the configuration file to $HADOOP_HOME/conf

```
$ cp randomwriter_conf.xsl workGenKeyValue_conf.xsl $HADOOP_HOME/conf
```

4.5.2 Installation and Configuration of Software

Step 1: Download and unload the pakage of software

mixWorkloadSuite.tar at tmp form

Step 2: Prepare the input data

Compile Mapreduce job WriteToHdfs.java for writing input data set

```
$ cd /tmp/mixWorkloadSuite/FB
$ mkdir hdfsWrite
$ javac -classpath ${HADOOP_HOME}/hadoop-${HADOOP _VERSION}-core.jar -d hdfsWrite WriteToHdfs..java jar -cvf WriteToHdfs.jar -C hdfsWrite/ .
```

Step 3: Edit randomwriter_conf.xsl using configuration parameters

```
$ cd $HADOOP_HOME/conf
$ vim randomwriter_conf.xsl
```

Make sure the "test.randomwrite.bytes_per_map" and "java GenerateReplayScript" files have the same [size of each input partition in bytes] parameter.

Step 4: Execute the following commands

```
$ bin/hadoop jar WriteToHdfs.jar org.apache.hadoop.examples.WriteToHdfs - conf conf/randomwriter_conf.xsl workGenInput
```

4.5.3 Generate the replay script

Step 1. Obtain a representative load

get-Job-Info.pl: This tool is used to analyze the default log format hadoop hadoop job history log data.

```
$ perl get-Job-Info.pl [job history dir] > outputFile.tsv
```

This script print to STDOUT, is used as a file into (outputFile.tsv) or further more in-depth analysis. This output file contents are divided by tap values (.tsv), the output file for each column as follows:

1.unique_Job_id
2.submit_time_seconds
3.inter_job_submit_gap_seconds
4.map_input_bytes
5.shuffle_bytes
6.reduce_output_bytes

Example of use:

```
$ perl get-Job-Info.pl sort_LogRepository > outputFile.tsv
```

Description: sort Log Repository is the log file on the hadoop cluster running sort jobs directory on the local file system.

Import data [Workload trace processing] to give the log file [cleanup workload trace, extract the information needed]:

```
$ FB-2009_samplesBySort_24_times_1hr_0.tsvoutputFile.tsv
$ FB-2009_samples_24_times_1hr_0.tsv => FB-2009_samplesBySort_24_times_1hr_0.tsv
```

Use [matching] K-means clustering, a class of similar log file contains the contents of outputFile.tsv:

k_means_FB.py Use the format:

```
$ python k_means_FB.py logFile.tsv K > FB-2009_samplesKMSort_24_times_1hr_0.tsv
```

We find it N times the minimum loss value (K = 1,2, M) K = 10 to obtain the minimum time of the loss.

Example of use:

```
$ python k_means_FB.py FB-2009_samplesBySort_24_times_1hr_0.tsv 10 > FB-2009_samplesKMSort_24_times_1hr_0.tsv
```

Here, we provide a scripting tool run_clustering.sh and get_optimal_K.py to get the best K value. run_clustering.sh as follow:

```
$ ./ run_clustering.sh logFile.tsv [k Ranging from] [N Repetitions]
```

Example of use:

```
$ ./run_clustering.sh FB-2009_samplesBySort_24_times_1hr_0.tsv 1 20 50
```

Above script will generate/opt/mixWorkloadSuite/logfile/runlog_$k_$i+1.logfile, we use get_optimal_K.py. To analyze the /opt/mixWorkloadSuite/logfile/all files under optimal K value.

Example of use:

$python get_optimal_K.py /opt/mixWorkloadSuite/logfile/

Being the most representative of the load

After we get the last section 3.1.3 K clusters of log files, this stage needs to extract from this file contains a class file outputFile.tsv in content.

getTraceBySpecies_FB.py

Use the format

$python getTraceBySpecies_FB.py FB-2009_samplesKMSort_24_times_1hr_0.tsv > FB-2009_samplesKMBySort_24_times_1hr_0.tsv

Step 2: Use GenerateReplayScriptFB.java to create a folder that in-cludes the script of executable workload

$ cd /tmp/mixWorkloadSuite/FB

$ javac GenerateReplayScriptFB.java

$ java GenerateReplayScriptFB [Workload file]

[Actual number of services generating clusters] [Number of testing clusters services from user] [Input division size (byte)]

[Input number of divisions] [Generated replay scripts catalog] [Inputted data directory on HDFS file system] [Workload output mark on HDFS file system] [Data amount of every reduce task] [workload standard error output directory] [Hadoop command]

[Directory of WorkGen.jar]

[Directory of workGenKeyValue_conf.xsl]

Workloadfile:

[path to synthetic workload file] for testing, e.g FB-2009_samplesKMBySort_24_times_1hr_0.tsv

Actual number of services generating clusters:

[number of machines in the original production cluster]

Number of testing clusters services from user:

[number of machines in the cluster where the workload will be run]

Input division size (byte):

[size of each input partition in bytes] Should be roughly the same as HDFS block size, e.g., 67108864 Input number of divisions:

[number of input partitions] The input data size need to be >= max input size in the synthetic workload. Try a number. The program will check whether it is large enough. e.g., 10 for the workload in FB-2009_samplesKMBySort_24_times_1hr_0.tsv Generated replay scripts catalog:

[output directory for the scripts] e.g., scriptsTestFB

Inputted data directory on HDFS file system:

[HDFS directory for the input data] e.g., workGenInput. Later, need to generate data to this directory. Workload output mark on HDFS file system:

[prefix to workload output in HDFS] e.g., workGenOutputTest. The HDFS output dir will have format $prefix-$jobIndex. Data amount of every reduce task::

[amount of data per reduce task in byptes] Should be roughly the same as HDFS block size, e.g., 67108864 workload standard error output directory:

[workload output dir] Directory to output the log files, e.g., /home/USER/swimOutput.

Hadoop command:

[hadoop command] Command to invoke Hadoop on the targeted system, e.g. $HADOOP_HOME/bin/hadoop

Directory of WorkGen.jar:

[path to WorkGen.jar] Path to WorkGen.jar on the targeted system, e.g. $HADOOP_HOME/WorkGen.jar

Directory of workGenKeyValue_conf.xsl:

[path to workGenKeyValue_conf.xsl] Path to workGenKeyValue_conf.xsl on the targeted system, e.g. $HADOOP_HOME/conf/workGenKeyValue_conf.xs

Step 3: Prepare replay scripts for Google workload traces

When use BigDataBench-multitenancy, we need to prepare scripts to workload replay. Here we use GenerateReplayScriptGoogle.java to generate the replay scripts

```
$ cd /tmp/mixWorkloadSuite/Google
$ Javac GenerateReplayScriptGoogle.java
$ Java  GenerateReplayScriptGoogle
[workload file directory]
[replay scripts catalog]
[shark commad]
```

4.5.4 Workload replay in BigDataBench-multitenancy

Execute workload replay, just execute mixWorkloadReplay.sh using command line. Using method

```
$ cd /tmp/mixWorkloadSuite/FB
$ cp -r scriptsTestFB $HADOOP_HOME
$ cd /tmp/mixWorkloadSuite/Google
$ cp -r scriptsTestGoogle $HADOOP_HOME
$ ./mixWorkloadReplay.sh argment(f/g or m)
```

4.6 Simulator Version

Simics is a full-system simulator used to run unchanged production binaries of the target hardware at high-performance speeds. It can simulate systems such as Alpha, x86-64, IA-64, ARM, MIPS (32- and 64-bit), MSP430, PowerPC (32-and 64-bit), POWER, SPARC-V8 and V9, and x86 CPUs.

We use SPARC as the instruction set architecture in our Simics version simulator benchmark suite, and deploy Solaris operation systems

1) Simics installation

It is recommended to install in the /opt/virtutech directory

Step 1. Download the appropriate Simics installation package from the download site, such as simics-pkg-00-3.0.0-linux.tar

Step 2. Extract the installation package, the command is as follows:

```
$ tar xf simics-pkg-00-3.0.0-linux.tar
```

It Will add a temporary installation directory, called simics-3.0-install

Step 3. Enter the temporary installation directory, run the install script, the command is as follows

```
$ cd simics-3.0-install $ sh install-simics.sh
```

Step 4. The Simics requires a decryption key, which has been unpacked before.

decode key has been cached in $HOME/.simics-tfkeys.

```
$ HOME/.simics-tfkeys
```

Step 5. When the installation script is finished, Simics has been installed in the /opt/virtutech/simics-<version>/, if the previous step to specify the installation path, this path will be different

2) Workloads

In the simulator version we provide the following workloads in our images, which is called BigDataBench Subset.

No.	Workload name
1	Hadoop-WordCount
2	Hadoop-Grep
3	Hadoop-NaiveBayes
4	Cloud-OLTP-Read
5	Hive-Diﬀ er
6	Hive-TPC-DS-query3
7	Spark-WordCount
8	Spark-Sort
9	Spark-Grep
10	Spark-Pagerank
11	Spark-Kmeans
12	Shark-Project
13	Shark-Orderby
14	Shark-TPC-DS-query8
15	Shark-TPC-DS-query10
16	Impala-Orderby
17	Impala-SelectQuery

3) Workloads running

Get Images Get Images from http://prof.ict.ac.cn/bdb_uploads/master. tar.gz and http://prof.ict.ac.cn/bdb_uploads/slaver.tar.gz Decompress the packages.

```
$ tar -zxvf master.tar.gz
$ tar -zxvf slaver.tar.gz
```

Start the workloads

Users can use the following commands to drive the Simics images and start the workloads:

Hadoop Based workloads

Experimental environment

Cluster: one master one slaver,

Software : We have already provide the following software in our images.

Hadoop version: Hadoop-1.0.2

ZooKeeper version: ZooKeeper-3.4.5

Hbase version: HBase-0.94.5
Java version: Java-1.7.0
Running command

Workload	Master	Slaver
Wordcount	cd /master	cd /slaver
	./simics -c Hadoopwordcount_L	./simics -c Hadoopwordcount_L
	bin/hadoop jar $HADOOP_HOME/ hadoop-examples-*.jar wordcount /in /out/wordcount	
Grep	cd /master	cd /slaver
	./simics -c Hadoopgrep_L	./simics -c Hadoopgrep _LL
	bin/hadoop jar $HADOOP_HOME/ hadoop-examples-*.jar grep /in /out/g rep a*xyz	
NaiveBayes	cd /master	cd /slaver
	./simics -c HadoopBayes_L	./simics -c HadoopBayes_LL
	bin/mahout testclassifier -m /model -d /testdata	
Cloud OLTP-Read	cd /master	cd /slaver
	./simics -c YCSBRead_L	./simics -c YCSBRead _LL
	./bin/ycsb run hbase -P workloads/workloadc -p operationcount=1000 -p hosts=10.10.0.13 -p columnfamily=f1 -threads 2 -s>hbase_tranunlimited C1G.dat	

Hive based workloads
Experimental environment
Cluster: one master one slaver
Hadoop version: Hadoop-1.0.2

Hive version: Hive-0.9.0
Java version: Java-1.7.0
Running command

Workload	Master	Slaver
Hive-Differ	cd /master	cd /slaver
	./simics HiveDiffer_L	./simics -c HiveDiffer_LL
	./BigOP-e-commerce-difference.sh	
Hive-TPC-DS-query3	cd /master	cd /slaver
	./simics -c Hadoopgrep_L	./simics -c Hadoopgrep_LL
	./query3.sh	

Spark based version
Experimental environment
Cluster: one master one slaver
Hadoop version: Hadoop-1.0.2
Spark version: Spark-0.8.0
Scala version: Scala-2.9.3
Java version: Java-1.7.0
Running command

Workload	Master	Slaver
Spark-WordCount	cd /master	cd /slaver
	./simics -c SparkWordcount_L	./simics -c SparkWordcount_LL
	./run-bigdatabench cn.ac.ict.bigdatabench.WordCount spark://10.10.0.13:7077 /in /tmp/wordcount	
Spark-Grep	cd /master	cd /slaver
	./simics -c Sparkgrep_L	./simics -c Sparkgrep_LL
	./run-bigdatabench cn.ac.ict.bigdatabench.Grep spark://10.10.0.13:7077 /in lda_wiki1w /tmp/grep	

Spark-Sort	cd /master	cd /slaver
	./simics -c SparkSort_L	./simics -c SparkSort_LL
	./run-bigdatabench cn.ac.ict.bigdatabench.Sort spark://10.10.0.13:7077 /in /tmp/sort	
Spark-Pagerank	cd /master	cd /slaver
	./simics -c SparkPagerank_L	./simics -c SparkPagerank_LL
	./run-bigdatabench cn.ac.ict.bigdatabench.PageRank spark://10.10.0.13:7077 /Google_genGraph_5.txt /tmp/PageRank	
Spark-Kmeans	cd /master ./simics -c SparkKmeans_L	cd /slaver ./simics -c SparkKmeans_LL
	./run-bigdatabench org.apache.spark.mllib.clustering.KMeans spark://10.10.0.13:7077 /data 8 4	

Shark based workloads Experimental environment Cluster: one master one slaver Software:

Hadoop version: Hadoop-1.0.2

Spark version: Spark-0.8.0

Scala version: Scala-2.9.3

Shark version: Shark-0.8.0

Hive version: hive-0.9.0-shark-0.8.0-bin

Java version: Java-1.7.0

Running command

Workload	Master	Slaver
Shark-Project Shark-Orderby	cd /master	cd /slaver
	./simics -c Sharkprojectorder_L	./simics -c Sharkprojectorder_LL
	./runMicroBenchmark.sh	
Shark-TPC-	cd /master	cd /slaver

DS-query8		
	./simics -c Sharkproquery8_L shark -f query8.sql	./simics -c Sharkquery8_LL
Shark-TPC-DS-query10	cd /master	cd /slaver
	./simics -c Sharkproquery10_L	./simics -c Sharkquery10_LL
	shark -f query10.sql	

4.7 Nutch Search Engine

4.7.1 Introduction

Search is a search engine model, which is used to evaluate datacenter and cloud computing systems.

Search v1.0 brings some simplicity in terms of installation, deployment and monitoring. Within this version, we are offering Search with everything inside and ready to go. Search consists of a search engine, a workload generator, and a comprehensive workload characterization tool—DCAngel.

i. Targeted Audience

This document is targeting two types of audiences:

– People who just want to use Search as a benchmark tool for evaluating their datacenter and cloud computing systems. This is for those who will directly use the provided Search benchmark directly to deploy it on their cluster.

– People who would like to modify the sources to fit their particular needs. You could use modified Search to do workloads characteristics analysis, add some functionality, or replace a component with another one.

ii. Structure of the document

This document goes on the following route:

– A detailed introduction will be given in 4.7.2, for people who have never used Search before.

– How to install Search version 1.0 is introduced in 4.7.3, for people who are not going to make any change to the provided Search.

– How to build an appliance on your own needs can be found in 4.7.4, for people who are going to modify some components of Search.

iii. Further Readings

The following links give more in-depth details about technologies used in Search v1.0.

– Nutch : http://nutch.apache.org
– Perf : https://perf.wiki.kernel.org/index.php/Main_Page
– Tomcat: http://tomcat.apache.org/
– Sqlite3: http://www.sqlite.org/
– Numpy: http://numpy.scipy.org/
– Matplotlib: http://matplotlib.sourceforge.net/

4.7.2 Search

i. Quick introduction

Search is a search engine site benchmark that implements the core functionality of a search engine site: providing indices and snapshot for a query term. It does not implement complementary services like crawling and ranking. It only has one kind of session — user's session, via which users can query terms. Search consists of three parts — a search engine, a workload generator and DCAngel.

The search engine is based on nutch which is an open source web-search software project. For Search v1.0, we use nutch-1.1 as the search engine's platform. The indices and snapshot we used in Search are generated by nutch-1.1 with SoGou Chinese corpus (http://www.sogou.com/labs/dl/t.html).

We get a real world search engine's trace from a user's log of SoGou (http://www.sogou.com/labs/dl/q.html). The workload generator can transform the real trace by specifying the query rate variation and terms' situation. The work-load generator can also replay the real or synthetic traces.

DCAngel is a comprehensive workload characterization tool. It can collect performance metrics and then write them into database for further analysis and visualization. We use perf to collect performance counters' data.

For further reading about Search, please look at the following site: http://prof.ncic.ac.cn/DCBenchmarks.

ii. Available implementations

You may find available information and descriptions about older Search versions at its home page (http://prof.ncic.ac.cn/DCBenchmarks). If newer version implemented, it will be appended.

4.7.3 Getting started

In this part, you will drive right into the configuration and running part, sup-posing you don't want to modify the provided Search.

i. Overview

Our experiment platform is based on Nutch's distributed search engine which is a typical two-tier web application. It off ers the following architecture:

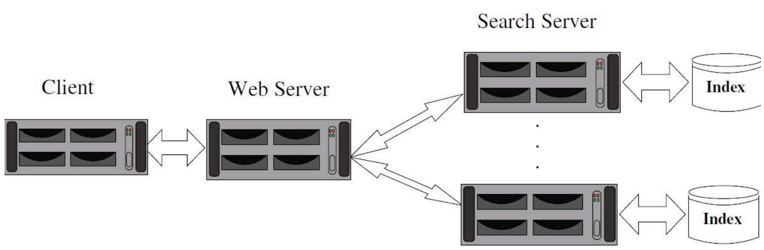


Fig. 1. Architecture of Search

– Client: injecting the workload thanks to the workload generator (written in python) and collecting metric results by DCAngel.

– Web Server: receiving HTTP requests from clients and dispatching them to Search Servers. We use Apache Tomcat 6.0.26 as the front end and nutch-1.1 as the search engine.

– Search Server: serving client requests transmitting by Web Server and the return the results to Web Server

ii. Prerequisites

The provided Search v1.0 relies on perf, JDK, Python and Numpy. In this part, we focus on how you can use what is provided in the Search-v1.0 package, for deeper information you may go over the Building part in 4.7.4.

Tomcat 6.0.26 and nutch-1.1 are included in our package, so the user should not prepare them.

ii.a. Linux Kernel Version

For this step, you need to get the root privileges for your Linux servers.

We need to build a linux kernel whose version is 2.6.31 or newer for all the Search Server nodes, because those kernels support perf_events port, which is used by perf. When you compare the kernel, you should make sure that perf_events is build into your kernel.

ii.b. perf

For perf , users should get a linux kernel source code whose version is 2.6.31 or newer on all Search Server nodes and then enter the directory tools/perf. After that, users should execute the following commands to install perf :

```
$ make
$ make install
```

ii.c. Python

All the linux systems need Python whose version is 2.7. Older or newer versions haven't been verified in our system.

ii.d. Numpy

The Client node needs Numpy (http://numpy.scipy.org/), which is the fundamental package needed for scientific computing with Python. You may need the following libraries or tools before installing Numpy:

atlas, python-nose, lapack, blas, libgfortran, python-dateutil, python-matplotlib, python-tz, python-setuptools

ii.e. Matplotlib

The Client node needs matplotlib(http://matplotlib.sourceforge.net/), which is a python 2D plotting library.

ii.f. JAVA

Java 1.6.x, preferably from Sun, must be installed in all linux systems except Client node. You should also set JAVA_HOME to the ans42 user.

ii.g. CPU

For this version, the Search Server nodes' CPU type must be as below:

Intel Xeon processor 3000, 3200, 5100, 5300 series

Intel Core 2 duo processor

If you use other CPUs, you may go over the CPU part in 4.7.4.

ii.h. SSH

SSH must be installed and sshd must be running. To run the Search scripts that manage remote daemons, please make sure that you can ssh on remote nodes without entering password

ii.i. Setup passphraseless ssh

Client node must ssh to Web server and Search Server nodes without a passphrase, Now check that.

```
$ ssh localhost
```

If you cannot ssh to nodes without a passphrase, execute the following commands at Client node:

```
$ ssh-keygen -t dsa -f $HOME/.ssh/id_dsa -P ""
```

This should result in two files, $HOME/.ssh/id_dsa (private key) and $HOME/.ssh/id_dsa.pub (public key).

Copy $HOME/.ssh/id_dsa.pub to Web Server nodes and Search Server nodes

On those nodes run the following commands:

```
$ cat id_dsa.pub » $HOME/.ssh/authorized_keys2
$ chmod 0600 $HOME/.ssh/authorized_keys2
```

Depending on the version of OpenSSH the following commands may also be required:

```
$ cat id_dsa.pub » $HOME/.ssh/authorized_keys
$ chmod 0600 $HOME/.ssh/authorized_keys
```

An alternative is to create a link from authorized_keys2 to authorized_keys:

```
$ cd $HOME/.ssh && ln -s authorized_keys2 authorized_keys
```

On the Client node test the results by ssh'ing to other nodes:

```
$ ssh -i $HOME/.ssh/id_dsa server
```

This allows ssh access to the nodes without having to specify the path to the id_dsa file as an argument to ssh each time.

ii.j. Network

This should come as no surprise, but for the sake of completeness we have to point out that all the machines must be able to reach each other over the network. The easiest is to put all machines in the same network with regard to hardware and software configuration, for example connect machines via a single hub or switch and configure the network interfaces to use a common network such as 192.168.0.x=24.

To make it simple, we will access machines using their hostname, so you should write the IP address and the corresponding hostname into /etc/hosts. The fol-lowing is an example.

```
#/etc/hosts
10.10.104.47 gd47
10.10.104.48 gd48
10.10.104.49 gd49
10.10.104.50 gd50
```

iii. Deploying Search

You're suggested creating a new user for all Linux systems, and use the new user to do the following. To make it simple, we just assume the new user you created for the tool is ans42 with the password 'a'.

The user should download the Search-v1.0 package to the Client node using the user ans42. We assume that you put the decompressed package in the directory of $Search. All the following operations should be done in Client node.

iii.a. Configuration

To deploy Search, you should first configure the $Search/common.mk file as follow.

uname = ans42 # the user' s name for the benchmark upwd = a # the corresponding password of the user Master = gd88 # the Web Server node' s hostname

Node = gd48,gd49,gd88 # the hostname of Web Server node and Search Server nodes

Do not change other configurations in this file.

At last, execute "make deploy" and "source /.bashrc". Then Search will be deployed on all nodes. The deployment time depends on the number of nodes and the machine's hardware configuration. It maybe needs tens of minutes.

Before you running the benchmark, please make sure that the Web Server node's port 9090 is available or the Web Server node's firewall has already been closed.

iv. Running Benchmark

iv.a. Workload Preparation

Enter the $Search/exp directory and edit the run-test.sh file.

```
11 #———write your workload here—————————#
12 report search.example.head:100000-fixed:100@s?i2@reqs-SoGou
```

Here, we give an example of workload at line 12, which is also a default workload. You can go over the workload part of session 4 if you want to create a new workload yourself.

If you want to use the default workload, you should replace the "?" by the num-ber of Search Server nodes.

iv.b. Start benchmark test

Under the $Search/exp/ directory you should run the following command to start the benchmark test.

```
$ make test
```

The information of the test can be seen at file ./nohup.out

iv.c. Get result

We have integrated DCAngel, which is a comprehensive workload characteriza-tion tool in our Search benchmark. Now we can use it to collect performance date, aggregate data and visualize data.

Figure.2 shows the high-level diagram of DCAngel. It stores performance data in a relational database managed by SQLite3 that supports the extended SQL statements. Users can access those data through the extended SQL statements.

All the tests' log and performance data collected by DCAngel can be find in the $Search/exp/log/($workload) directory. The ($workload) here represents the workload you use. For example, if you use the default workload, the log can be find at exp/log/search.example.head:100000-fixed:100@s?i2@reqs-SoGou where "?" represents the Search server nodes' number. In that directory, there will be a file named exp-report if the test of the workload finished. The file is an empty file, and the only usage is to tell the user that workload replay has fin-ished. The exp-log file records the start time and end time of the workload. The search directory collect the search log, the terms send to search engine and warm-up log. The hmon directory collects performance data of Search Server nodes.

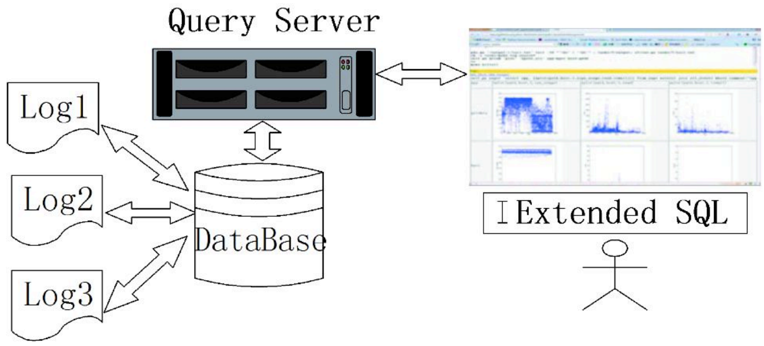
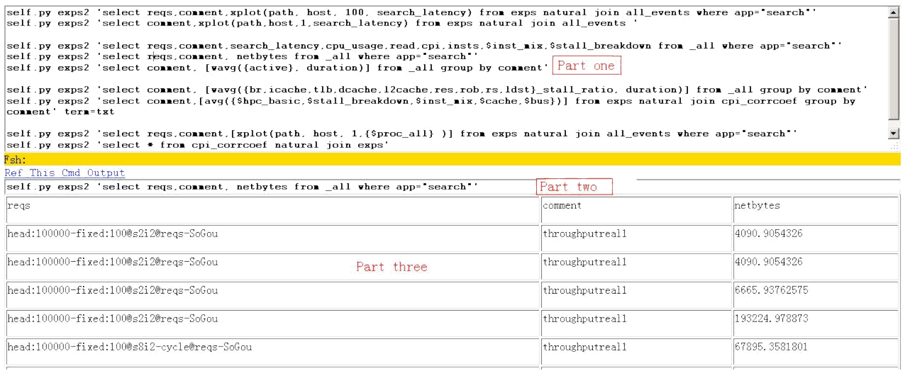


Fig. 2. High Level Diagram of DCAngel

Users can get data through a browser using DCAngel. For this version, the only



browser we supported is FireFox. First, you should start the service by executing the following commands.

Enter the directory python-lib/fsh/:

```
$ cd python-lib/fsh
```

Start the service: ./psh.py port. For the port, we use 8002 as a example.

```
$ ./psh.py 8002
```

And then you can visit DCAngel's browser port through the address (do not forget the slash after "fsh"):

The $Search above is the location of Search-v1.0 package.

Figure 3 shows the snapshot of DCAngel's GUI. The GUI can be divided into three parts. Part one is commands column. Each line in that column is a DCAngel command. Users can execute the command by ctrl+ left mouse button click. Users can edit those commands to meet your requirement. Part two is command

Fig. 3. snapshot of DCAngel's GUI

input column; you can input your command here and execute it by pressing Enter. Part three is a display column, which displays the result of the command. Now we will show you the DCAngel command's grammar, so that you can writer your own commands.

A DCAngel command has two parts-a fixed part and a SQL like part. Let us look at the following command as an example.

```
$ self.py exps2 'select reqs,comment, netbytes from _all where app="search" '
```

The fixed part is self.py exps2 and the SQL like part is 'select reqs,comment, netbytes from _all where app="search" '. For the SQL like part, users can write any statement that meets the sqlite3's syntax.

DCAngel's feedback may take a few seconds if it is your first time to execute a DCAngel command after a test. That is because DCAngel needs time to write metrics data it collected into database. DCAngel also defines many extend SQL functions. Those functions usage are shown as below.

std(arg1) : standard deviation of arg1
corrcoef(arg1, arg2) : correlation coeffi cient between arg1 and arg2
correlate(arg1,arg2) : cross correlation of arg1 and arg2
wavg(arg1,arg2): weighted average of arg1, and arg2 is weight
xplot(arg1, arg2, arg3, arg4) : draw the scatter figure of arg4. The x-axis of this figure is time and the y-axis is arg4' s average value. arg1 and arg2 should be "path" and "host" respective. arg3 is degree of data aggregation. If arg3 equals 100, each point in the figure represents the average value of 100 arg4. xhist(arg1, arg2, arg3, arg4) : draw the histogram of arg4' s occurrence times. The x-axis of this figure is occurrence times and the y-axis is arg4' s average value. arg1 and arg2 should be "path" and "host" respective. arg3 is degree of data aggregation. If arg3 equals 100, each value on the x-axis represents the average value of 100 arg4.
xscatter(arg1,arg2,arg3,arg4,arg5) : draw bi-dimensional histogram of arg4 and
arg5. arg1 and arg2 should be "path" and "host" respective. arg3 is degree of
data aggregation. If arg3 equals 100, each value on x-axis and y-axis represents
the average value of 100 arg4 and arg5.
xcorr(arg1,arg2,arg3,arg4,arg5) : plot the cross correlation between arg4 and arg5. arg1 and arg2 should be âĂ IJpathâĂ İ and "host" respective. arg3 is degree of data aggregation.

If you want to use xplot you must make sure that the following read color words are not changed:

self.py exps2 ' select reqs,comment,host, xplot(path, host, 1, $metric) from exps natural join all_events
self.py exps2 ' select reqs,comment,host, xhist(path, host, 1, $metric) from exps natural join all_events

self.py exps2 ’ select reqs,comment,host, xscatter(path, host, 1, $metric,$metic) from exps natural join all_events

self.py exps2 ’ select reqs,comment,host, xcorr(path, host, 1, $metric,$metric) from exps natural join all_events

For $metric it can be any $metircs can be any field in Appendix B

We list the table structure of DCAngel’s database in Appendix A. Users can look up Appendix A and write your own DCAngel command

4.7.4 Building your own Search

If you want to build your own Search, this part will give some advices.

i. CPU

If your Search Server nodes do not own a CPU whose type is one of the types we mentioned in 4.7.3, you should modify line 167 to line 201 of file $Search/hmon/hmon.py.

```
kperf_events_map = ”  ’
CPU_CLK_UNHALTED.CORE 3c # cpu_cycles
CPU_CLK_UNHALTED.BUS 13c # bus cycles
INST_RETIRED.ANY c0 # insets
ITLB_MISS_RETIRED c9 # itlb_misses
DTLB_MISSES.ANY 108 # dtlb_misses
L1I_MISSES 81 # icache_misses
L1D_REPL f45 # dcache_misses
L2_LINES_IN.ANY f024 # l2cache_misses
PAGE_WALKS.CYCLES 20c # page_walks
CYCLES_L1I_MEM_STALLED 86 # icache_stalls
BR_INST_RETIRED.ANY c4 # br_insts
BR_INST_RETIRED.MISPRED c5 # br_misses
INST_RETIRED.LOADS 1c0 # load_insts
INST_RETIRED.STORES 2c0 # store_insts
INST_RETIRED.OTHER 4c0 # other_insts
SIMD_INST_RETIRED.ANY 1fc7 # simd_insts
FP_COMP_OPS_EXE 10 # fp_insts
RESOURCE_STALLS.ANY 1fdc # res_stalls
RESOURCE_STALLS.ROB_FULL 1dc # rob_stalls
RESOURCE_STALLS.RS_FULL 2dc # rs_stalls
RESOURCE_STALLS.LD_ST 4dc # ldst_stalls
RESOURCE_STALLS.FPCW 8dc # fpcw_stalls
RESOURCE_STALLS.BR_MISS_CLEAR 10dc # br_miss_stalls
BUS_TRANS_ANY e070 # bus_trans
BUS_DRDY_CLOCKS 2062 # bus_drdy
BUS_BNR_DRV 2061 # bus_bnr
BUS_TRANS_BRD e065 # bus_trans_brd
BUS_TRANS_RFO e066 # bus_trans_rfo
```

" '

You should go over your CPU's software design manual and change hexadecimal number above to the corresponding CPU event number.

ii. Make your search engine

For default Search, we just supply a SoGou corpus's snapshot and indices and all the Search Server nodes have the same indices and snapshot (it also called segments in nutch). Your can use your corpus's snapshot and indices. With your snapshot and indices, you can separate the snapshot and index them by using the nutch command — merge and index. You should put each part of snapshot and index into Search Server nodes' /home/ans42/crawl/combinations directory. The default Search gives you an example of the indices and snapshot's layout in each Search Server node's directory: /home/ans42/crawl/combinations. After that, you should modify the configuration file s?i2.cfg in Cline node's $Search/nutch where '?' represents the number of Search Server nodes. The content of that configuration file is as follows:

```
1 server-list=gd87 gd88 gd89 gd90
2 gd87-crawl-dir=01
3 gd88-crawl-dir=23
4 gd89-crawl-dir=45
5 gd90-crawl-dir=67
```

The first line represents the Search Servers' hostnames. From the second line, each defines the directory name of corresponding Search Server node's snap-shot and index.

iii. Creating your own workload

4.7.3 mentions you can create your own workload, and this section will explains how to create a workload.

Now we will show how to create a workload by show the syntax and explaining a given workload's meaning. The given workload is as follows:

```
Syntax:
search.#anno.function1(:args)-function2(:args)@configfile@reqfile
An example:
search. instance.head:10000-poisson:20@s8i2@reqs-sogou
```

"search" means that a search engine is under evaluation. We use dot(.) to link diff erent parts.

"#anno" is the annotation of this workload; in the example we use "instance" to indicate that this workload is an instance.

"function1(:args)-function2(:args)" indicates the functions we use to the real re-quest sequence. "function1" and "function2" is transforming function's name. The function can be found at Appendix C. "args" is the function's parame-ters. we use "-" to link transforming functions. In the example "head:10000 " means that we use head function in Appendix C, head function's parameter is "10000 ". "poisson:20 " means that we use poisson function in Appendix C and its parameter is "20"

"@configfile" indicates the configuration file we used for Search Server. The configuration file is in Client node's $Search/nutch directory.. In the example "@s8i2

" means that we use s8i2.cfg as Search Server nodes' configuration file where s8i2.cfg is in Client node's $Search/nutch directory.

"@reqfile" indicates the original request sequence we use. The request sequence file is in Client node's $Search/search-engine/data directory. Appendix D lists the request sequence we have provided, and users can use one of them or a new one. In the example, "@reqs-sogou" means that we use sogou request and the request file is $Search/search-engine/data/reqs-sogou.

You can use all the function in Appendix C to create your own workload, and adopt your own Search Server nodes' configuration file and request. For how to configure Search Server nodes you can consult 4.7.4.

4.7.5 Appendix A - Metrics collected by DCAngel

variable	Definition
	Metrics from performance counters
cpu_cycles	Core cycles when core is not halted
bus_cycles	Bus cycles when core is not halted
insts	Retired instructions
itlb_misses	Retired instructions that missed the ITLB
dtlb_misses	Memory accesses that missed the DTLB
icache_misses	Instruction Fetch Unit misses
dcache_misses	L1 data cache misses
page_walks	Duration of page-walks in core cycles
icache_stalls	Cycles during which instruction fetches stalled
br_insts	Retired branch instructions
br_misses	Retired mispredicted branch instructions.
load_insts	Instructions retired, which contain a load
store_insts	Instructions retired, which contain a store
other_insts	Instructions retired, which no load or store operation
simd_insts	Retired Streaming SIMD instructions
fp_insts	Floating point computational micro-ops executed
res_stalls	Resource related stalls
rob_stalls	Cycles during which the reorder buff er full
rs_stalls	Cycles during which the reserve station full
ldst_stalls	Cycles during which the pipeline has exceeded load or store limit or waiting to commit all stores
fpcw_stalls	Cycles stalled due to floating-point unit control word writes
br_miss_stalls	Cycles stalled due to branch misprediction
bus_trans	All bus transactions
bus_drdy	Bus cycles when data is sent on the bus
bus_bnr	Number of Bus Not Ready signals asserted
bus_trans_brd	Burst read bus transactions
bus_trans_rfo	Read For Ownership bus transactions
	Metrics from /proc filesystem
usr	User mode CPU time
nice	The CPU time of processes whose nice value is
sys	Kernel mode CPU time
idle	Idle time
iowait	Iowait time
irq	Hard interrupt time

softirq	Soft interrupt time
intr	The times of interrupt happened
ctx	Context switch times
procs	Process number
running	The number of processes that is running
blocked	The number of processes that is blocked
mem_total	Total memory
free	Memory that is not used
buffers	Size memory in buffer cache
cached	Memory that cache used
swap_cached	Memory that once was swapped out, but still in the swapfile
active	Memory that has been used more recently
inactive	Memory that is not active
swap_total	Total amount of physical swap memory
swap_free	Total amount of free swap memory
pgin	The number of pages that paged in from disk
pgout	The number of pages that paged out to disk
pgfault	The number of page fault
pgmajfault	The number of major page faults
active_conn	TCP active connection
passive_conn	TCP passive connection
rbytes	Received bytes
rpackets	Received packets
rerrs	Received error packets number
rdrop	Number of packets dropped by native network adapter
sbytes	Bytes sent
spackets	Packets sent
serrs	Number of error packets sent
sdrop	Number of packets dropped by remote network adapter
read	Times of disk reads
read_merged	Times of disk merged reads
read_sectors	Times of sectors read
read_time	The total time disk read
write	Times of disk writes
write_merged	Times of merged disk writes
write_sectors	Times of sectors write
write_time	The total time of disk write

4.7.6 Appendix B - DCAngel database table structure

For the meaning of all following table's abbreviations, users can go over Appendix A.

Table exps

field	Definition
path	The test performance data's path under exp/ directory
app	User used application's name
comment	The comment when user used to specify a
reqs	Request name
duration	The test's duration
host	Node's host name

Table _all

Field	Definition
path	The test performance data's path under exp/ directory
host	Node's host name
insts	The mean value of instruction number
cpi	Cycles per instruction
br_miss_ratio	Branch miss ratio
br_stall_ratio	Branch stall ratio
icache_stall_ratio	Icache stall ratio
tlb_stall_ratio	TLB stall ratio
dcaceh_stall_ratio	Dcache stall ratio
l2cache_stall_ratio	L2 Cache stall ratio
res_stall_ratio	Resource related stall ratio
rob_stall_ratio	Reorder buff er stall ratio
rs_stall_ratio	Reserve station stall ratio
ldst_stall_ratio	Load and store stall ratio
fpcw_stall_ratio	Float point unit stall ratio
br_mix	Branch instruction ratio
load_mix	Load instruction ratio
store_mix	Store instruction ratio
ldst_mix	Load and store instruction ratio
simd_mix	SIMD instruction ratio
fp_mix	Float point instruction ratio
other_mix	Instructions that except load and store ratio
bus_util	Bus utilization
bus_d_util	bus_drdy ratio users can find bus_drdy and all the following abbreviations' meaning in Appendix A
bus_bnr_ratio	bus_bnr ratio
bus_brd_ratio	bus_brd ratio
bus_rfo_ratio	bus_rfo_ratio
cpu_usage	CPU utilization
search_latency	Average query latency
search_start	Test start time

duration	The test's duration
netbytes	rnetbytes+snetbytes
netpackets	rnetpacket+snetpacket

For table_all, we also define some macro which you can use to simplify your inputting.

For example you can write a DCAngel command self.py exps2 'select $prim from _all ', which has the same function with self.py exps2 'select app, comment, reqs, host from _all'

Macros and their definitions

macros	definition
$prim	app, comment, reqs, host
$hpc_basic	insts, cpi, br_miss_ratio
$stall_breakdown	br_stall_ratio, icache_stall_ratio, tlb_stall_ratio, dcache_stall_ratio, l2cache_stall_ratio, res_stall_ratio, rob_stall_ratio, rs_stall_ratio, ldst_stall_ratio, fpcw_stall_ratio
$inst_mix	br_mix, load_mix, store_mix, ldst_mix, simd_mix, fp_mix, other_mix
$cache	itlb_miss_ratio, dtlb_miss_ratio, icache_miss_ratio, dcache_miss_ratio, l2cache_miss_ratio
$bus	bus_util, bus_d_util, bus_bnr_ratio, bus_brd_ratio, bus_rfo_ratio
$proc_basic	cpu_usage, iowait, ctx, active, pgfault, pgmajfault
$net	active_conn, passive_conn, netbytes, netpackets,
$disk	read, write, read_sectors, write_sectors
$proc_selected	cpu_usage,iowait,ctx,active,pgmajfault,read_sectors
$hpc_all	$hpc_basic, $cache, $bus, $inst_mix
$proc_all	$proc_basic,$net,$disk