# Alibaba Cloud E-MapReduce

## Best Practices

Issue: 20190918

# Legal disclaimer

**Alibaba Cloud reminds you to carefully read and fully understand the terms and conditions of this legal disclaimer before you read or use this document. If you have read or used this document, it shall be deemed as your total acceptance of this legal disclaimer.**

1. **You shall download and obtain this document from the Alibaba Cloud website or other Alibaba Cloud-authorized channels, and use this document for your own legal business activities only. The content of this document is considered confidential information of Alibaba Cloud. You shall strictly abide by the confidentiality obligations. No part of this document shall be disclosed or provided to any third party for use without the prior written consent of Alibaba Cloud.**
2. **No part of this document shall be excerpted, translated, reproduced, transmitted, or disseminated by any organization, company, or individual in any form or by any means without the prior written consent of Alibaba Cloud.**
3. **The content of this document may be changed due to product version upgrades , adjustments, or other reasons. Alibaba Cloud reserves the right to modify the content of this document without notice and the updated versions of this document will be occasionally released through Alibaba Cloud-authorized channels. You shall pay attention to the version changes of this document as they occur and download and obtain the most up-to-date version of this document from Alibaba Cloud-authorized channels.**
4. **This document serves only as a reference guide for your use of Alibaba Cloud products and services. Alibaba Cloud provides the document in the context that Alibaba Cloud products and services are provided on an "as is", "with all faults " and "as available" basis. Alibaba Cloud makes every effort to provide relevant operational guidance based on existing technologies. However, Alibaba Cloud hereby makes a clear statement that it in no way guarantees the accuracy, integrity , applicability, and reliability of the content of this document, either explicitly or implicitly. Alibaba Cloud shall not bear any liability for any errors or financial losses incurred by any organizations, companies, or individuals arising from their download, use, or trust in this document. Alibaba Cloud shall not, under any circumstances, bear responsibility for any indirect, consequential, exemplary, incidental, special, or punitive damages, including lost profits arising from the use**

or trust in this document, even if Alibaba Cloud has been notified of the possibility of such a loss.

5. By law, all the content of the Alibaba Cloud website, including but not limited to works, products, images, archives, information, materials, website architecture, website graphic layout, and webpage design, are intellectual property of Alibaba Cloud and/or its affiliates. This intellectual property includes, but is not limited to, trademark rights, patent rights, copyrights, and trade secrets. No part of the Alibaba Cloud website, product programs, or content shall be used, modified , reproduced, publicly transmitted, changed, disseminated, distributed, or published without the prior written consent of Alibaba Cloud and/or its affiliates . The names owned by Alibaba Cloud shall not be used, published, or reproduced for marketing, advertising, promotion, or other purposes without the prior written consent of Alibaba Cloud. The names owned by Alibaba Cloud include, but are not limited to, "Alibaba Cloud", "Aliyun", "HiChina", and other brands of Alibaba Cloud and/or its affiliates, which appear separately or in combination, as well as the auxiliary signs and patterns of the preceding brands, or anything similar to the company names, trade names, trademarks, product or service names, domain names, patterns, logos, marks, signs, or special descriptions that third parties identify as Alibaba Cloud and/or its affiliates).
6. Please contact Alibaba Cloud directly if you discover any errors in this document.

# Generic conventions

Table -1: Style conventions

| Style | Description | Example |
| --- | --- | --- |
|  | This warning information indicates a situation that will cause major system changes, faults, physical injuries, and other adverse results. |  Danger:<br>Resetting will result in the loss of user configuration data. |
|  | This warning information indicates a situation that may cause major system changes, faults, physical injuries, and other adverse results. |  Warning:<br>Restarting will cause business interruption. About 10 minutes are required to restore business. |
|  | This indicates warning information, supplementary instructions, and other content that the user must understand. |  Notice:<br>Take the necessary precautions to save exported data containing sensitive information. |
| | This indicates supplemental instructions, best practices, tips, and other content that is good to know for the user. |  Note:<br>You can use Ctrl + A to select all files. |
| > | Multi-level menu cascade. | Settings > Network > Set network type |
| Bold | It is used for buttons, menus , page names, and other UI elements. | Click OK. |
| `Courier font` | It is used for commands. | Run the `cd /d C:/windows` command to enter the Windows system folder. |
| *Italics* | It is used for parameters and variables. | `bae log list --instanceid` *Instance_ID* |
| [] or [a\|b] | It indicates that it is a optional value, and only one item can be selected. | `ipconfig` *[-all\|-t]* |

| Style | Description | Example |
| --- | --- | --- |
| {} or {a\|b} | It indicates that it is a required value, and only one item can be selected. | `swich {stand \| slave}` |

# Contents

# 1 Use E-MapReduce to collect metrics from a Kafka client

This section describes how to use E-MapReduce to collect metrics from a Kafka client to conduct effective performance monitoring.

## Background

Kafka provides a collection of metrics that are used to measure the performance of Broker, Consumer, Producer, Stream, and Connect. E-MapReduce collects metrics for Kafka Broker by using Ganglia to monitor the running status of this Kafka Broker. A Kafka system consists of two roles: a Kafka Broker and multiple Kafka clients. When an issue of read/write performance occurs, you must perform an analysis on the both Kafka Broker and clients. Metrics from Kafka clients are important for performing the analysis.

## Principle

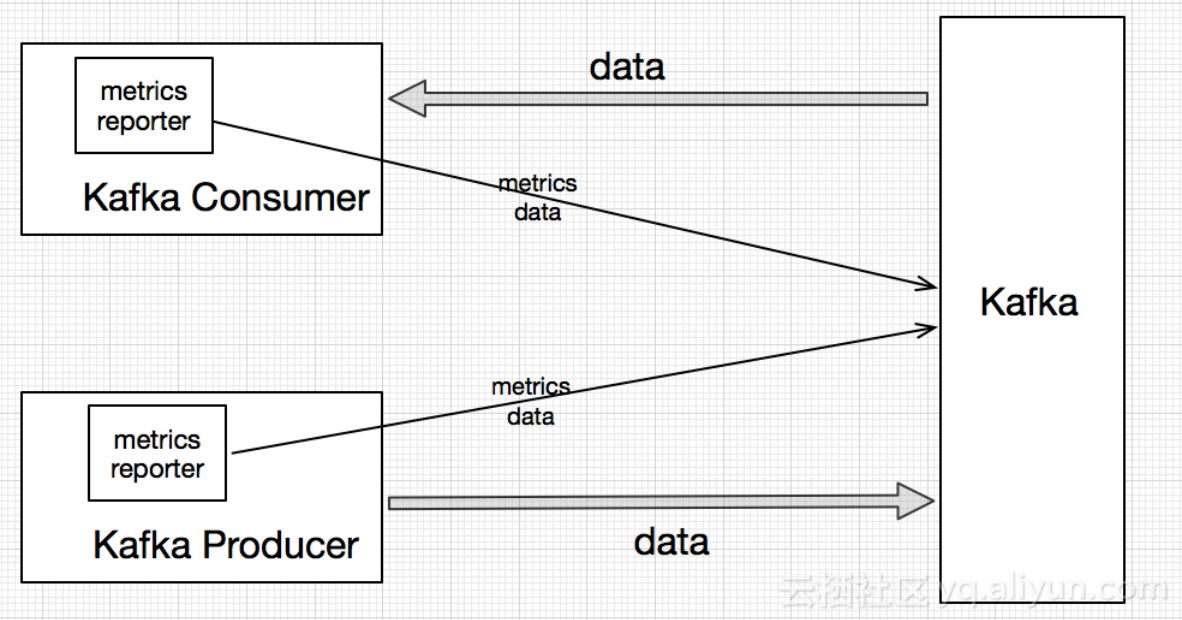
- Collect Metrics for Kafka performance

  Kafka supports multiple external Metrics Reporters. JMX Reporter is built in to Kafka by default. You can use the JMX tool to view metrics of Kafka. You can implement your own Metrics Reporter such as `org.apache.kafka.common.metrics.MetricsReporter` to collect custom metrics.

- Store Metrics

  You can customize Kafka metrics. In addition, you need a data store to keep these metrics for later use and analysis. You can store metrics to Kafka without using a third-party data store as Kafka itself is a data store. In addition, Kafka can be

easily integrated with other services. You can collect metrics from a client as the following figure shows:



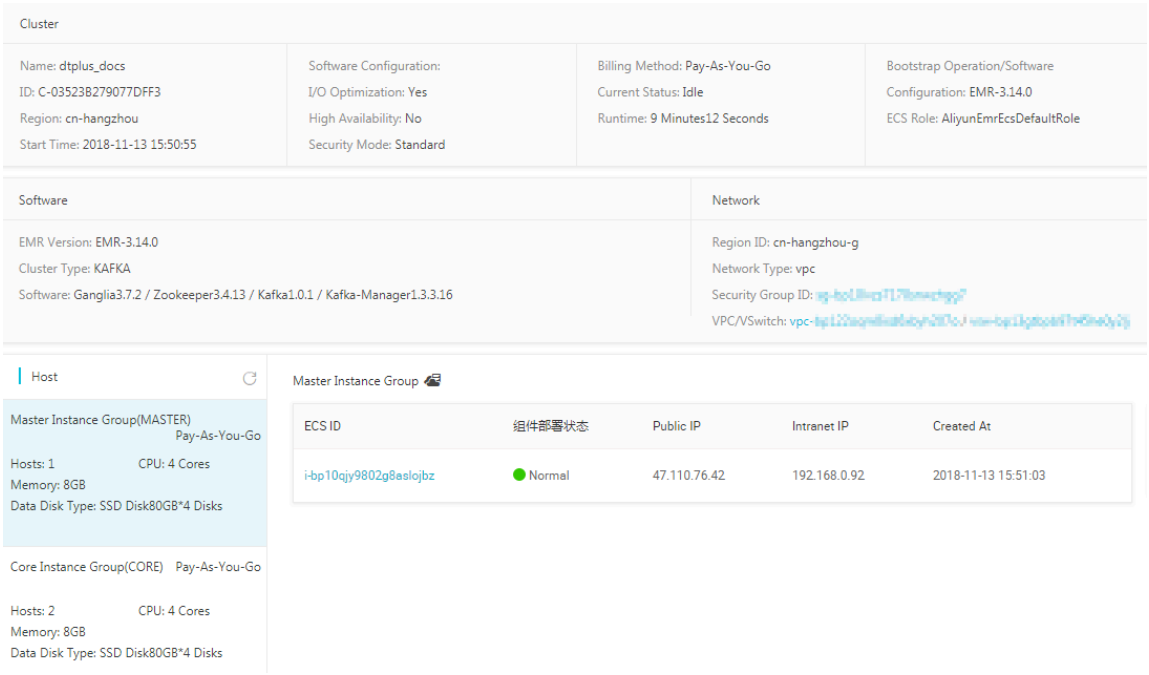

## Prerequisites

- Restrictions
  - Support for only Java applications;
  - Support for only clients of Kafka 0.10 or later;
- Without compiling code by yourself, E-MapReduce has published the jar package in Maven. You can download the latest version from the download link.

- In this section, we use E-MapReduce to automatically create a Kafka cluster. For more information, see Create a cluster.

  We use the following versions of E-MapReduce and Kafka:

  - EMR Version: EMR-3.12.1
  - Cluster Type: Kafka
  - Software: Kafka-Manager (1.3.3.16), Kafka (2.11-1.0.1), ZooKeeper (3.4.12), and Ganglia (3.7.2)
  - The network type of this Kafka cluster is VPC in the China (Hangzhou) region. The master instance group is configured with a public IP and an internal network IP. The following figure shows the details.




- Configure metrics

| Metric | Description |
| --- | --- |
| `metric . reporters` | The sample Metrics Reporter: `org . apache . kafka . clients . reporter . EMRClientMetricsReporter` |
| `emr . metrics . reporter . bootstrap . servers` | The metrics that stores bootstrap.servers of a Kafka cluster. |
| `emr . metrics . reporter . zookeeper . connect` | The metrics that stores Zookeeper addresses of a Kafka cluster. |

- Load metrics
  - Place the emr-kafka-client-metrics jar package on a client. Add the path of the jar package to the classpath of a client-side application.
  - Install the emr-kafka-client-metrics dependency on the jar package of a client-side application.

## Procedures

1. Download the latest emr-kafka-client-metrics package.

```
wget   http :// central . maven . org / maven2 / com / aliyun / emr
/ emr - kafka - client - metrics / 1 . 4 . 3 / emr - kafka - client
- metrics - 1 . 4 . 3 . jar
```

2. Create a test topic.

```
kafka - topics . sh  -- zookeeper   emr - header - 1 : 2181 / kafka
- 1 . 0 . 1  -- partitions   10  -- replicatio  n - factor   2  --
topic   test - metrics   -- create
```

3. Copy the *emr - kafka - client - metrics* package to the lib directory of a Kafka client.

```
cp   emr - kafka - client - metrics - 1 . 4 . 3 . jar  / usr / lib
/ kafka - current / libs /
```

4. Write data to a test topic. You can write the configurations of a Kafka Producer to the local client.conf file.

```
##  client . conf :
 metric . reporters = org . apache . kafka . clients . reporter .
 EMRClientM  etricsRepo  rter
 emr . metrics . reporter . bootstrap . servers = emr - worker - 1 :
 9092
 emr . metrics . reporter . zookeeper . connect = emr - header - 1 :
 2181 / kafka - 1 . 0 . 1
 bootstrap . servers = emr - worker - 1 : 9092
##  Commnad :
 kafka - producer - perf - test . sh  -- topic   test - metrics  --
 throughput   1000  -- num - records   100000
-- record - size   1024  -- producer . config   client . conf
```

5. View the current metrics from a client. The default metrics topic is *_emr - client - metrics* .

```
 Kafka - console - consumer . sh  --  Topic   _   emr - client -
 metrics  --  Bootstrap - server   emr - worker - 1 :  9092
```

```
-- from - beginning
```

The returned message is shown as follows.

```
{ prefix = kafka . producer ,  client . ip = 192 . 168 . xxx . xxx
 ,  client . process = 25536 @ emr - header - 1 . cluster - xxxx ,
 attribute = request - rate ,  value = 894 . 4685104965  012 ,
 timestamp = 1533805225  045 ,  group = producer - metrics ,
 tag . client - id = producer - 1 }
```

Note:

| Field name | Description: |
| --- | --- |
| client.ip | The IP address of a client host. |
| client.process | The process ID of a client-side application. |
| attribute | The attribute name of a metric. |
| value | The value of a metric. |
| timestamp | The timestamp when you collect a metric. |
| tag.xxx | Other tag information of a metric. |

# 2 Use E-MapReduce to process offline jobs

This section describes how to use E-MapReduce to read data from OSS, and a set of offline data processing operations, such as data collection and data clean-up.

## Overview

E-MapReduce clusters can be used in various scenarios. E-MapReduce supports all the scenarios that the Hadoop ecosystem and Spark support. E-MapReduce is based on Hadoop and Spark clusters. You can use Alibaba Cloud ECS instances hosted by E-MapReduce clusters in the same way as you would on your physical machines.

Two popular kinds of big data processing that we use today are offline and online data processing.

- Offline data processing: You only want to obtain the analytical results of data without a major concern about the time it takes. For example, in a batch data processing scenario, you receive data from OSS and output processing results to OSS, using MapReduce, Hive, Pig, and Spark.
- Online data processing: You want to obtain the analytical results of data with a strict requirement on the time it takes, such as real-time streaming data processing . Deeply integrated with Spark MLlib, GrapX, and SQL, Spark Streaming can be used to process streaming messages.

This section describes how to run an offline job called word count in E-MapReduce.

## Process

OSS -> EMR -> Hadoop MapReduce

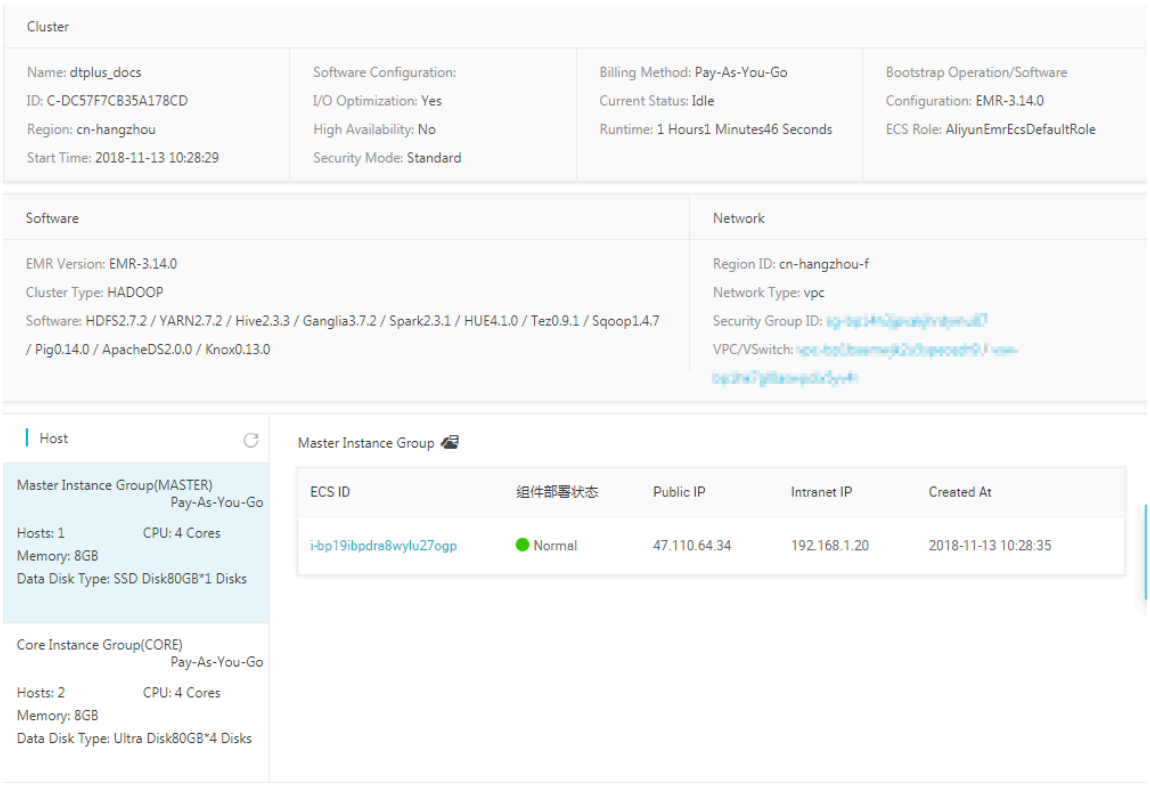
This process includes two steps:

1. Store data to OSS.
2. Read data from OSS and analyze the data by using E-MapReduce.

## Prerequisites

- The following steps are performed in a Windows system. You need to ensure that Maven and Java have been installed and configured properly into your system.

- You can use E-MapReduce to automatically create a Hadoop cluster. For more information, see Create a cluster.
  - EMR Version: EMR-3.12.1
  - Cluster Type: HADOOP
  - Software: HDFS2.7.2, YARN2.7.2, Hive2.3.3, Ganglia3.7.2, Spark2.3.1, HUE4.1.0, Zeppelin0.8.0, Tez0.9.1, Sqoop1.4.7, Pig0.14.0, ApacheDS2.0.0, and Knox0.13.0
  - The network type of this Hadoop cluster is VPC in the China (Hangzhou) region. The master instance group is configured with a public IP and an internal network IP. The high availability mode is set to No (a non-HA mode). The following figure shows the details.




## Procedures

1. Download sample code to your local disk.

   Open git bash in your system and execute the clone command as follows.

   ```
   git clone https :// github . com / aliyun / aliyun - emapreduce - demo . git
   ```

   Execute the `mvn install` command to compile the code.

2. For more information about how to create a bucket, see Create a bucket.

   > **Note:**
   > You must create a bucket and an E-MapReduce cluster in the same region.

3. Upload jar packages and resource files

   a. Log on to the OSS console and click the Files tab.

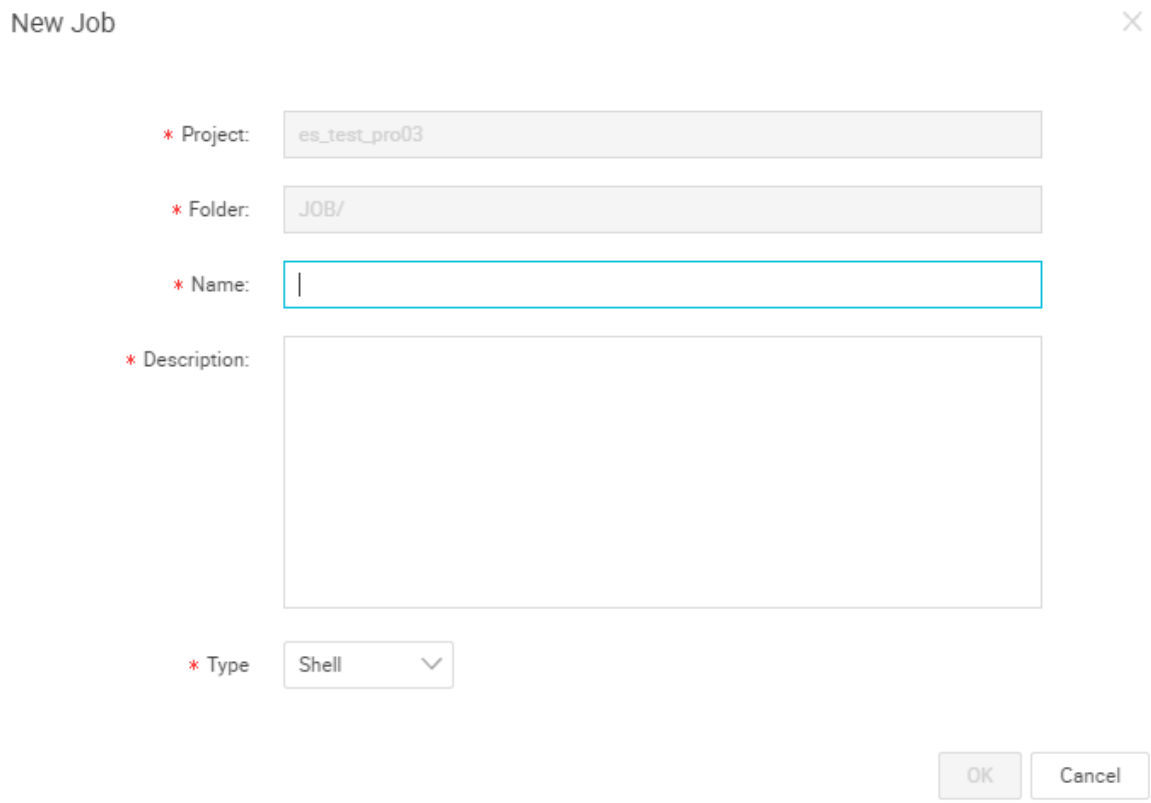
   b. Click Upload to upload resources files in the `aliyun-emapreduce-demo/resources` directory and jar packages in the `aliyun-emapreduce-demo/target` directory.

4. Create a workflow project

   For more information, see Workflow project management.

5. Create a job

   For more information, see Edit jobs. Take a MapReduce job as an example.



6. After you configure a job, click Run. The following figure shows the details.

   - For more information about how to use OSS, see #unique_7.
   - For more information about how to configure jobs, see the *job* section of the E-MapReduce User Guide.

   > Note:
   >
   > - If the OSS output URI already exists, an error occurs when you execute a job.
   > - When you click the Insert an OSS UNI button and select OSSREF as a File Prefix , E-MapReduce downloads OSS files to your cluster and add these files to a specified classpath.
   > - Currently, only OSS Standard storage is supported for all operations.

### View logs

For more information about how to view logs of an execution plan, see Connect to a cluster using SSH.

# 3 Submit Storm topologies to process data in Kafka on E-MapReduce

This topic describes how to deploy Storm clusters and Kafka clusters on E-MapReduce and run Storm topologies to consume data in Kafka.

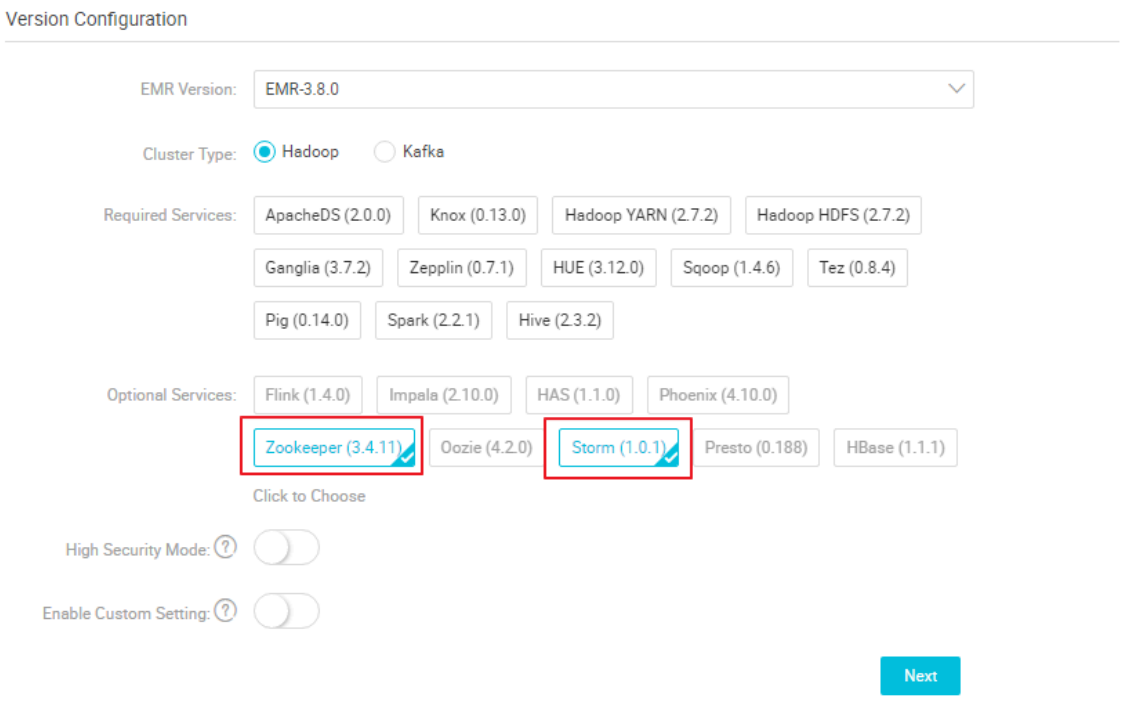
## Prepare the environment

The test is performed using EMR that is deployed in the China East 1 (Hangzhou) region. The version of EMR is 3.8.0. The component versions required for this test are as follows.

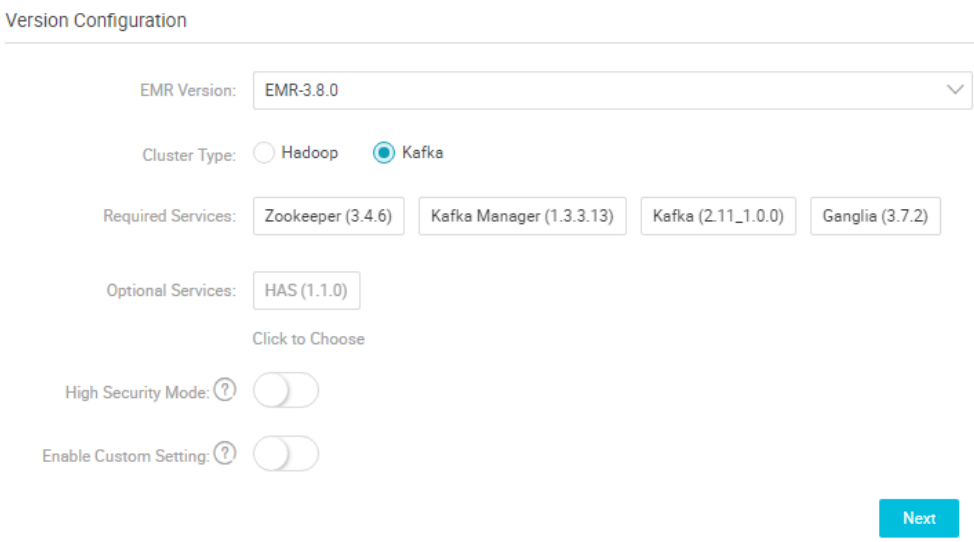
- Kafka: 2.11_1.0.0
- Storm: 1.0.1

In this topic, we use Alibaba Cloud E-MapReduce to create a Kafka cluster automatically. For more information, see Create a cluster.

- Create a Hadoop cluster



- Create a Kafka cluster




**Note:**

- If you choose classic network as the network type, put the Hadoop cluster and the Kafka cluster in the same security group to save time for configuring connections between instances.
- If you choose VPC as the network type, put the Hadoop cluster and the Kafka cluster in the same VPC and the same security group to save time for configuring a VPC peering connection.
- If you are familiar with networking and security groups for ECS, you can create configurations as needed.

- Configure the environment for Storm

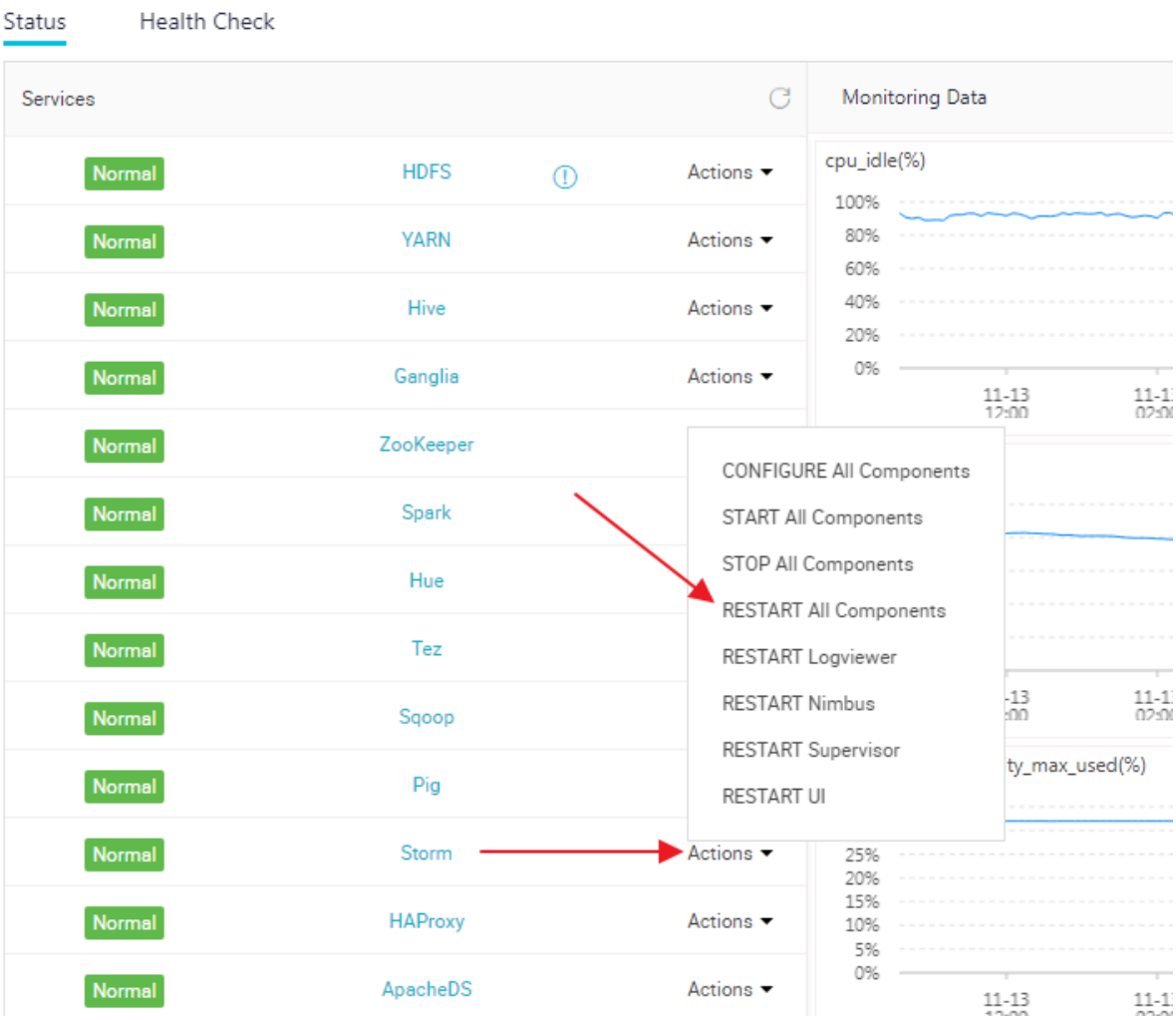
  Consuming Kafka data fails if you run Storm topologies in the initial environment. To avoid such failures, you need to install the following dependencies for the Storm environment:

  - curator-client
  - curator-framework
  - curator-recipes
  - json-simple
  - metrics-core
  - scala-library
  - zookeeper
  - commons-cli
  - commons-collections
  - commons-configuration
  - htrace-core
  - jcl-over-slf4j
  - protobuf-java
  - guava
  - hadoop-common
  - kafka-clients
  - kafka
  - storm-hdfs
  - storm-kafka

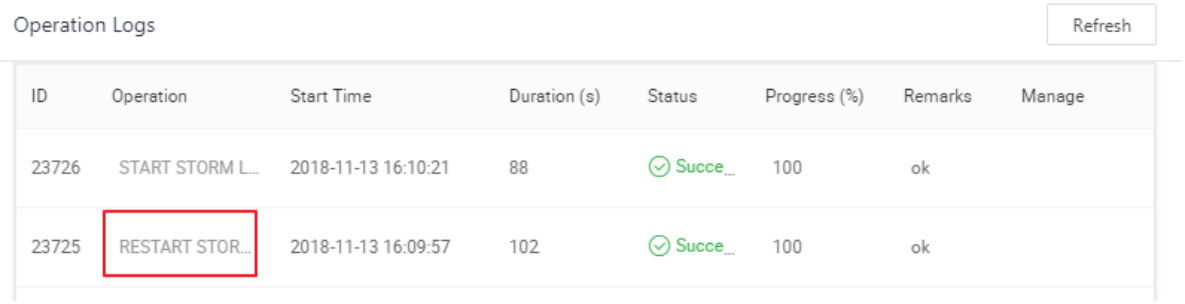
  These dependencies have been tested. If you need additional dependencies, perform the following operations to add them to the lib folder of Storm.

```
[hadoop@emr-header-1 ~]$ ll
total 8524
-rw-rw-r-- 1 hadoop hadoop   52988 Jun 14  2015 commons-cli-1.3.1.jar
-rw-rw-r-- 1 hadoop hadoop  588337 Nov 13  2015 commons-collections-3.2.2.jar
-rw-rw-r-- 1 hadoop hadoop  298829 Feb  5  2009 commons-configuration-1.6.jar
-rw-r--r-- 1 root   root     73448 Feb  9 14:01 curator-client-2.10.0.jar
-rw-r--r-- 1 root   root    195437 Feb  9 14:01 curator-framework-2.10.0.jar
-rw-r--r-- 1 root   root    281476 Feb  9 14:01 curator-recipes-2.10.0.jar
-rw-rw-r-- 1 hadoop hadoop   31212 Apr 19  2014 htrace-core-3.0.4.jar
-rw-rw-r-- 1 hadoop hadoop   17289 Jun 11  2012 jcl-over-slf4j-1.6.6.jar
-rw-rw-r-- 1 hadoop hadoop   16046 Aug 13  2009 json-simple-1.1.jar
-rw-rw-r-- 1 hadoop hadoop   82123 Nov 27  2012 metrics-core-2.2.0.jar
-rw-rw-r-- 1 hadoop hadoop  533455 Mar  8  2013 protobuf-java-2.5.0.jar
-rw-r--r-- 1 root   root   5745606 Feb  9 14:01 scala-library-2.11.7.jar
-rw-rw-r-- 1 hadoop hadoop  792964 Feb 24  2014 zookeeper-3.4.6.jar
[hadoop@emr-header-1 ~]$ pwd
/home/hadoop
[hadoop@emr-header-1 ~]$ sudo cp ./* /usr/lib/storm-current/lib/
```

You need to perform the preceding operations on each node in the Hadoop cluster. After the operations are complete, restart Storm in the E-MapReduce console as shown in the following figure.




You can view operation logs to check the status of Storm:




### Create Storm topologies and Kafka topics

- E-MapReduce provides sample code that you can use directly. The links are as follows:
  - e-mapreduce-demo
  - e-mapreduce-sdk
- Write data to topics
  1. Log on to the Kafka cluster.
  2. Create a test topic with 10 partitions and 2 replicas.

```
/ usr / lib / kafka - current / bin / kafka - topics . sh  --
 partitions   10  -- replicatio  n - factor   2  -- zookeeper
 emr - header - 1 :/ kafka - 1 . 0 . 0  -- topic   test  -- create
```

  3. Write 100 records of data to the test topic.

```
/ usr / lib / kafka - current / bin / kafka - producer - perf
 - test . sh  -- num - records   100  -- throughput   10000  --
 record - size   1024  -- producer - props   bootstrap . servers =
 emr - worker - 1 : 9092  -- topic   test
```

> **Note:**
> The preceding command is run on the emr-header-1 node in the Kafka cluster. You can also run the command on client nodes.

- Run a Storm topology.

  Log on to the Hadoop cluster, compile the project and copy the `examples - 1 . 1 - shaded . jar` file that under `/ target / shaded` directory to the emr-header-1 node. In this example, the file is stored in the HDFS root directory. Run the following command to submit the topology:

```
/ usr / lib / storm - current / bin / storm   jar   examples - 1 . 1
 - shaded . jar   com . aliyun . emr . example . storm . StormKafka
```

```
Sample   test   aaa . bbb . ccc . ddd   hdfs :// emr - header - 1 :
9000   sample
```

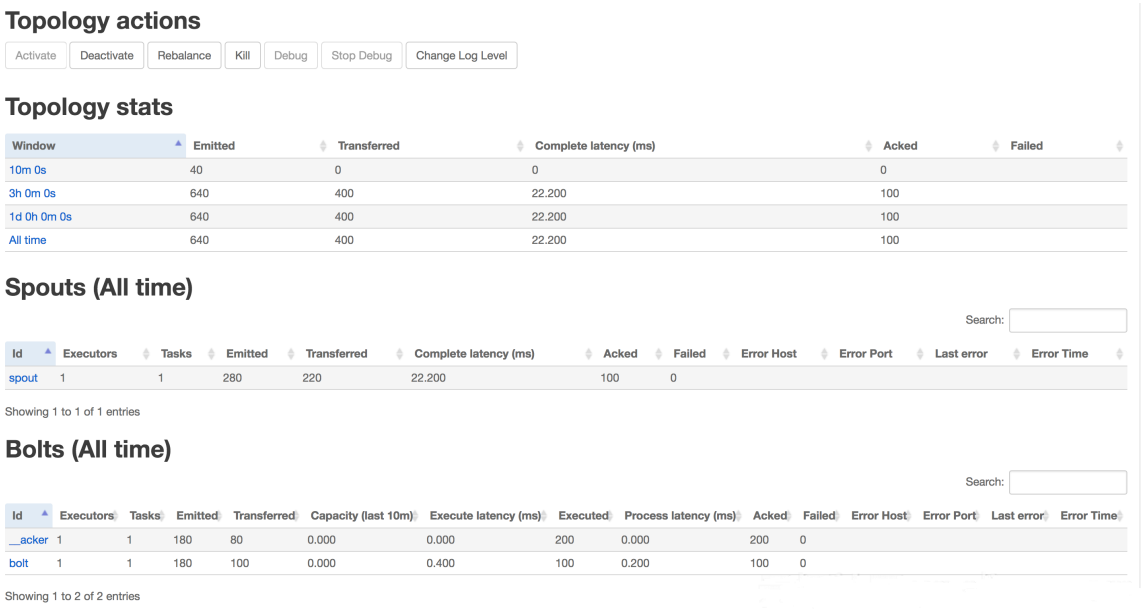
- View the running status of a topology
  - View the running status of Storm

    You can use the Web UI to view the services on a cluster in the following ways:

    ■ With Knox. For more information, see Knox instructions.

    ■ Use SSH. For more information, see Use SSH to log on to a cluster.

    In this topic, we use SSH to access the Web UI. The endpoint is *http :// localhost : 9999 / index . html* . You can see the topology that we have submitted. Click the topology to view the running logs:




  - View the output files in HDFS

    ■ View the output files in HDFS.

```
[ root @ emr - header - 1  ~]#  hadoop   fs  - ls  / foo /
- rw - r -- r --    3   root   hadoop       615000   2018 - 02
 - 11   13 : 37  / foo / bolt - 2 - 0 - 1518327393  692 . txt
- rw - r -- r --    3   root   hadoop       205000   2018 - 02
 - 11   13 : 37  / foo / bolt - 2 - 0 - 1518327441  777 . txt
[ root @ emr - header - 1  ~]#  hadoop   fs  - cat  / foo /
 bolt - 2 - 0 - 1518327441  777 . txt  |  wc  - l
 200
```

    ■ Write 120 records of data to the test topic in Kafka.

```
[ root @ emr - header - 1  ~]# / usr / lib / kafka - current
 / bin / kafka - producer - perf - test . sh  -- num - records
   120  -- throughput   10000  -- record - size   1024  --
 producer - props   bootstrap . servers = emr - worker - 1 :
 9092  -- topic   test
```

```
120 records sent , 816 . 326531 records / sec ( 0 . 80
  MB / sec ), 35 . 37 ms avg latency , 134 . 00 ms
max latency , 35 ms 50th , 39 ms 95th , 41 ms
99th , 134 ms 99 . 9th .
```

- Output the line number of the HDFS file.

```
[ root @ emr - header - 1 ~]# hadoop fs - cat / foo /
 bolt - 2 - 0 - 1518327441 777 . txt | wc - l
 320
```

## Summary

We have successfully deployed a Storm cluster and a Kafka cluster on E-MapReduce , run a Storm topology and consumed Kafka data. E-MapReduce also supports the Spark streaming and the Flink components, which can run in Hadoop clusters and process Kafka data.

**Note:**

E-MapReduce does not provide the Storm cluster option. Therefore, we have created a Hadoop cluster and have installed the Storm components. If you do not need to use other components, you can easily disable them in the E-MapReduce console. Then a Hadoop cluster is equivalent to a Storm cluster.

# 4 Use ES-Hadoop on E-MapReduce

ES-Hadoop is a tool used to connect the Hadoop ecosystem provided by Elasticsearch (ES). It enables users to use tools such as MapReduce (MR), Spark, and Hive to process data in ES (ES-Hadoop also supports taking a snapshot of ES indices and storing it in HDFS, which is not discussed in this topic).

## Background

We know that the advantage of the Hadoop ecosystem is processing large data sets. But the disadvantage is also obvious: interactive analysis can be delayed. ES is adept at many types of queries, especially ad-hoc queries. Subsecond response time has been reached. ES-Hadoop has combined both advantages. With ES-Hadoop, users only need to make small changes to the code for quickly processing data stored in ES. ES also provides acceleration.

ES-Hadoop uses ES as the data source of data processing engines, such as MR, Spark, and Hive. ES plays the role of storage in architectures where compute and storage are separated. This is the same for other data sources of MR, Spark, and Hive. But ES has faster data filtering ability compared with other data sources. This ability is one of the most critical abilities of an analytics engine.

EMR has already integrated with ES-Hadoop. Users can use ES-Hadoop directly without any configurations. The following examples introduce ES-Hadoop on EMR.

## Preparation

ES can automatically create indices and identify data types based on input data. In some cases, this feature is helpful, by avoiding many actions by users. However, it also cause problems. The biggest problem is that sometimes the data types identified by ES are not correct. For example, we define a field called `age`. The data type of this column is INT but it may be identified as LONG in the ES index. Users need to convert data types when performing some specified actions. We recommend that you create indices manually to avoid such problems.

In the following examples, we use the `company` index and the `employees'` type (you can consider an ES index as a database and a type as a table in the database). This type defines four fields (field types are defined by ES).

```
{
```

```
  " id ":  long ,
  " name ":  text ,
  " age ":  integer ,
  " birth ":  date
}
```

Run the following commands to create an index in Kibana (you can also use cURL commands):

```
 PUT   company
{
  " mappings ": {
    " employees ": {
      " properties ": {
        " id ": {
          " type ": " long "
        },
        " name ": {
          " type ": " text ",
          " fields ": {
            " keyword ": {
              " type ": " keyword ",
              " ignore_abo  ve ":  256
            }
          }
        },
        " birth ": {
          " type ": " date "
        },
        " addr ": {
          " type ": " text "
        }
      }
    }
  },
  " settings ": {
    " index ": {
      " number_of_  shards ": " 5 ",
      " number_of_  replicas ": " 1 "
    }
  }
}
```

**Note:**

Specify the index parameters in settings as needed. This step is optional.

Prepare a file where each row is a JSON object as follows:

```
{" id ":  1 , " name ": " zhangsan ", " birth ": " 1990 - 01 - 01 ", "
 addr ": " No .  969 ,  wenyixi   Rd ,  yuhang ,  hangzhou "}
{" id ":  2 , " name ": " lisi ", " birth ": " 1991 - 01 - 01 ", "
 addr ": " No .  556 ,  xixi   Rd ,  xihu ,  hangzhou "}
{" id ":  3 , " name ": " wangwu ", " birth ": " 1992 - 01 - 01 ", "
 addr ": " No .  699   wangshang   Rd ,  binjiang ,  hangzhou "}
```

Save the file to the specified directory in HDFS (for example, */ es - hadoop / employees . txt* ).

### Mapreduce

In the following example, we read the JSON files in the `/es-hadoop` directory in HDFS and write each row in the JSON files into ES as a document. Writing is finished in the map stage through EsOutputFormat.

Use the following options to set ES.

- es.nodes: ES nodes. The formats is host:port. For ES hosted on Alibaba Cloud, set the value to the endpoint of ES provided by Alibaba Cloud.
- es.net.http.auth.user: Username.
- es.net.http.auth.pass: Password.
- es.nodes.wan.only: For ES hosted on Alibaba Cloud, set the value to `true`.
- es.resource: The indices and types of ES.
- es.input.json: If the input file is in JSON format, set the value to `true`. Otherwise, you need to parse the input data using the map() function and output the corresponding Writable class.

 **Notice:**

**Disable speculative execution for map tasks and reduce tasks**

```
package com.aliyun.emr;

import java.io.IOExceptio n;
import org.apache.hadoop.conf.Configurat ion;
import org.apache.hadoop.fs.Path;
import org.apache.hadoop.io.NullWritab le;
import org.apache.hadoop.io.Text;
import org.apache.hadoop.mapreduce.Job;
import org.apache.hadoop.mapreduce.Mapper;
import org.apache.hadoop.mapreduce.lib.input.
FileInputF ormat;
import org.apache.hadoop.mapreduce.lib.input.
TextInputF ormat;
import org.apache.hadoop.util.GenericOpt ionsParser;
import org.apache.hadoop.util.Tool;
import org.apache.hadoop.util.ToolRunner;
import org.elasticsea rch.hadoop.mr.EsOutputFo rmat;

public class Test implements Tool {

  private Configurat ion conf;

 @Override
  public int run(String[] args) throws Exception {

    String[] otherArgs = new GenericOpt ionsParser(conf,
args).getRemaini ngArgs();

    conf.setBoolean("mapreduce.map.speculativ e", false);
```

```
    conf . setBoolean (" mapreduce . reduce . speculativ  e ",  false
);
    conf . set (" es . nodes ", "< your_es_ho  st >: 9200 ");
    conf . set (" es . net . http . auth . user ", "< your_usern  ame
>");
    conf . set (" es . net . http . auth . pass ", "< your_passw  ord
>");
    conf . set (" es . nodes . wan . only ", " true ");
    conf . set (" es . resource ", " company / employees ");
    conf . set (" es . input . json ", " yes ");

    Job   job  =  Job . getInstanc  e ( conf );
    job . setInputFo  rmatClass ( TextInputF  ormat . class );
    job . setOutputF  ormatClass ( EsOutputFo  rmat . class );
    job . setMapOutp  utKeyClass ( NullWritab  le . class );
    job . setMapOutp  utValueCla  ss ( Text . class );
    job . setJarByCl  ass ( Test . class );
    job . setMapperC  lass ( EsMapper . class );

    FileInputF  ormat . setInputPa  ths ( job ,  new   Path (
otherArgs [ 0 ]));

    return   job . waitForCom  pletion ( true ) ?  0  :  1 ;
 }

 @ Override
  public   void   setConf ( Configurat  ion   conf ) {
    this . conf  =  conf ;
 }

 @ Override
  public   Configurat  ion   getConf () {
    return   conf ;
 }

  public   static   class   EsMapper   extends   Mapper < Object ,
Text ,  NullWritab  le ,  Text > {
    private   Text   doc  =  new   Text ();

   @ Override
    protected   void   map ( Object   key ,  Text   value ,  Context
  context )  throws   IOExceptio  n ,  Interrupte  dException  {
      if  ( value . getLength () >  0 ) {
        doc . set ( value );
        context . write ( NullWritab  le . get (),  doc );
     }
   }
 }

  public   static   void   main ( String []  args )  throws
Exception  {
    int   ret  =  ToolRunner . run ( new   Test (),  args );
    System . exit ( ret );
  }
}
```

**Compile and package the code into a JAR file called *mr - test . jar* . Submit it to an instance that has installed an EMR client program (such as a gateway, or any node in an EMR cluster).**

Run the following commands on any node that has installed an EMR client to run the MapReduce program:

```
hadoop jar mr - test . jar com . aliyun . emr . Test -
Dmapreduce . job . reduces = 0 - libjars mr - test . jar / es -
hadoop
```

At this point, writing data to ES has finished. You can query the written data through Kibana ( or by using the cURL commands).

```
GET
{
  " query ": {
    " match_all ": {}
  }
}
```

### Spark

In this example, we write data to an index in ES using Spark instead of MapReduce. Spark persists a resilient distributed dataset (RDD) to ES using the JavaEsSpark class. Users also need to use the options mentioned above in the MapReduce section to set ES.

```
package com . aliyun . emr ;

import java . util . Map ;
import java . util . concurrent . atomic . AtomicInte ger ;
import org . apache . spark . SparkConf ;
import org . apache . spark . SparkConte xt ;
import org . apache . spark . api . java . JavaRDD ;
import org . apache . spark . api . java . function . Function ;
import org . apache . spark . sql . Row ;
import org . apache . spark . sql . SparkSessi on ;
import org . elasticsea rch . spark . rdd . api . java .
JavaEsSpar k ;
import org . spark_proj ect . guava . collect . ImmutableM ap ;

public class Test {

  public static void main ( String [] args ) {
    SparkConf conf = new SparkConf ();
    conf . setAppName (" Es - test ");
    conf . set (" es . nodes ", "< your_es_ho st >: 9200 ");
    conf . set (" es . net . http . auth . user ", "< your_usern ame
>");
    conf . set (" es . net . http . auth . pass ", "< your_passw ord
>");
    conf . set (" es . nodes . wan . only ", " true ");

    SparkSessi on ss = new SparkSessi on ( new SparkConte
xt ( conf ));
    final AtomicInte ger employeesN o = new AtomicInte ger
( 0 );
    JavaRDD < Map < Object , ? >> javaRDD = ss . read (). text ("
hdfs :// emr - header - 1 : 9000 / es - hadoop / employees . txt ")
```

```
        . javaRDD (). map (( Function < Row ,  Map < Object , ?
 >>)  row  ->  ImmutableM  ap . of (" employees " +  employeesN  o .
 getAndAdd ( 1 ),  row . mkString ()));

     JavaEsSpar  k . saveToEs ( javaRDD , " company / employees ");
  }
}
```

Package the code in a JAR file called spark-test.jar. Run the following command to write data:

```
spark - submit  -- master   yarn  -- class   com . aliyun . emr .
Test   spark - test . jar
```

After the task has finished, you can query the results through Kibana or the cURL commands.

In addition to `Spark RDD` . ES-Hadoop also provides a Spark SQL component to read and write ES data. For more information, see the official website of ES-Hadoop.

### Hive

This example introduces SQL statements to read and write ES data through Hive.

First, run the `hive` command to enter CLI and create a table:

```
CREATE   DATABASE   IF   NOT   EXISTS   company ;
```

Then create an external table that is stored in ES. Specify the option using TBLPROPERTIES.

```
CREATE   EXTERNAL   table   IF   NOT   EXISTS   employees (
  id   BIGINT ,
  name   STRING ,
  birth   TIMESTAMP ,
  addr   STRING
)
STORED   BY  ' org . elasticsea  rch . hadoop . hive . EsStorageH
andler '
TBLPROPERT  IES (
   ' es . resource ' = ' tpcds / ss ',
   ' es . nodes ' = '< your_es_ho  st >',
   ' es . net . http . auth . user ' = '< your_usern  ame >',
   ' es . net . http . auth . pass ' = '< your_passw  ord >',
   ' es . nodes . wan . only ' = ' true ',
   ' es . resource ' = ' company / employees '
);
```

**Note:**

We set the data type of the birth columns to TIMESTAMP in the Hive table. In ES, we set it to DATE. This is because Hive and EC handle data types differently. Parsing of converted date data can fail when Hive writes data to ES. In contrast, parsing of

returned data can also fail when Hive reads ES data. For more information, click here .

Insert some data into the table:

```
INSERT INTO TABLE employees VALUES ( 1 , " zhangsan ", "
1990 - 01 - 01 "," No . 969 , wenyixi Rd , yuhang , hangzhou
");
INSERT INTO TABLE employees VALUES ( 2 , " lisi ", " 1991 -
01 - 01 ", " No . 556 , xixi Rd , xihu , hangzhou ");
INSERT INTO TABLE employees VALUES ( 3 , " wangwu ", " 1992
- 01 - 01 ", " No . 699 wangshang Rd , binjiang , hangzhou ");
```

Execute queries to view the results:

```
SELECT * FROM employees LIMIT 100 ;
OK
1 zhangsan 1990 - 01 - 01 No . 969 , wenyixi Rd ,
yuhang , hangzhou
2 lisi 1991 - 01 - 01 No . 556 , xixi Rd , xihu
, hangzhou
3 wangwu 1992 - 01 - 01 No . 699 wangshang Rd ,
binjiang , hangzhou
```

# 5 Use Mongo-Hadoop on E-MapReduce

Mongo-Hadoop is a component provided by MongoDB for Hadoop components to connect to MongoDB. Using Mongo-Hadoop is similar to using ES-Hadoop which is described in the previous topic. EMR has already integrated with Mongo-Hadoop. Users can directly use Mongo-Hadoop without any deployment configuration. This topic describes how to use Mongo-Hadoop using some examples.

## Preparation

We use the same data model for the following examples:

```
{
  " id ":  long ,
  " name ":  text ,
  " age ":  integer ,
  " birth ":  date
}
```

We write data into the specified collection (similar to a table in a database) in a MongoDB database. Therefore, we need to first ensure that the collection exists in the MongoDB database. First, run the MongoDB client program on a client node that can access the MongoDB database. You may need to download the client program from the MongoDB website and install it. Take the connection to ApsaraDB for MongoDB as an example:

```
mongo  -- host   dds - xxxxxxxxxx  xxxxxxxxxx  x . mongodb . rds .
aliyuncs . com : 3717  -- authentica  tionDataba  se   admin  - u
root  - p   123456
```

The hostname of the MongoDB database is dds-xxxxxxxxxxxxxxxxxxxxx.mongodb.rds.aliyuncs.com. The port number is 3717. The actual port number depends on the MongoDB cluster. For an external MongoDB cluster that you have deployed on your own, the default port number is 27017. In this example, the password is set to 123456 using the -p option. Run the following commands in CLI to create a collection named employees in the company database:

```
>  use   company ;
>  db . createColl  ection (" employees ")
```

Prepare a file where each row is a JSON object as follows.

```
{" id ":  1 , " name ": " zhangsan ", " birth ": " 1990 - 01 - 01 ", "
 addr ": " No .  969 ,  wenyixi   Rd ,  yuhang ,  hangzhou "}
```

```
{" id ":  2 , " name ": " lisi ", " birth ": " 1991 - 01 - 01 ", "
 addr ": " No .  556 ,  xixi   Rd ,  xihu ,  hangzhou "}
{" id ":  3 , " name ": " wangwu ", " birth ": " 1992 - 01 - 01 ", "
 addr ": " No .  699   wangshang   Rd ,  binjiang ,  hangzhou "}
```

Save the file to the specified directory on HDFS (for example, the file path can be */ mongo - hadoop / employees . txt* ).

### Mapreduce

In the following example, we read JSON files in the */ mongo - hadoop* directory on HDFS and write each row in the JSON files as a document to the MongoDB database.

```
package   com . aliyun . emr ;

import   com . mongodb . BasicDBObj  ect ;
import   com . mongodb . hadoop . MongoOutpu  tFormat ;
import   com . mongodb . hadoop . io . BSONWritab  le ;
import   java . io . IOExceptio  n ;
import   org . apache . hadoop . conf . Configurat  ion ;
import   org . apache . hadoop . fs . Path ;
import   org . apache . hadoop . io . Text ;
import   org . apache . hadoop . mapreduce . Job ;
import   org . apache . hadoop . mapreduce . Mapper ;
import   org . apache . hadoop . mapreduce . lib . input .
FileInputF  ormat ;
import   org . apache . hadoop . mapreduce . lib . input .
TextInputF  ormat ;
import   org . apache . hadoop . util . GenericOpt  ionsParser ;
import   org . apache . hadoop . util . Tool ;
import   org . apache . hadoop . util . ToolRunner ;

public   class   Test   implements   Tool  {

  private   Configurat  ion   conf ;

 @ Override
  public   int   run ( String []  args )  throws   Exception  {

    String []  otherArgs  =  new   GenericOpt  ionsParser ( conf ,
args ). getRemaini  ngArgs ();

    conf . set (" mongo . output . uri ", " mongodb ://< your_usern
ame >:< your_passw  ord >@ dds - xxxxxxxxxx  xxxxxxxxxx  x . mongodb
. rds . aliyuncs . com : 3717 / company . employees ?  authSource =
admin ");

    Job   job  =  Job . getInstanc  e ( conf );
    job . setInputFo  rmatClass ( TextInputF  ormat . class );
    job . setOutputF  ormatClass ( MongoOutpu  tFormat . class );
    job . setOutputK  eyClass ( Text . class );
    job . setMapOutp  utValueCla  ss ( BSONWritab  le . class );

    job . setJarByCl  ass ( Test . class );
    job . setMapperC  lass ( MongoMappe  r . class );

    FileInputF  ormat . setInputPa  ths ( job ,  new   Path (
otherArgs [ 0 ]));

    return   job . waitForCom  pletion ( true ) ?  0  :  1 ;
```

```
  }

  @ Override
   public   Configurat  ion   getConf () {
     return   conf ;
  }

  @ Override
   public   void   setConf ( Configurat  ion   conf ) {
     this . conf  =  conf ;
  }

   public   static   class   MongoMappe  r   extends   Mapper < Object
 ,  Text ,  Text ,  BSONWritab  le > {

     private   BSONWritab  le   doc  =  new   BSONWritab  le ();
     private   int   employeeNo  =  1 ;
     private   Text   id ;

    @ Override
     protected   void   map ( Object   key ,  Text   value ,  Context
   context )  throws   IOExceptio  n ,  Interrupte  dException  {
       if  ( value . getLength () >  0 ) {
         doc . setDoc ( BasicDBObj  ect . parse ( value . toString
 ()));
         id  =  new   Text (" employee " +  employeeNo ++);
         context . write ( id ,  doc );
       }
     }
  }

   public   static   void   main ( String []  args )  throws
 Exception  {
     int   ret  =  ToolRunner . run ( new   Test (),  args );
     System . exit ( ret );
  }
}
```

**Compile and package the code into a JAR file called** *mr - test . jar* **. Run the following command:**

```
 hadoop   jar   mr - test . jar   com . aliyun . emr . Test  -
 Dmapreduce . job . reduces = 0  - libjars   mr - test . jar  / mongo
 - hadoop
```

**After the execution is complete, you can view the results using the MongoDB client program:**

```
>  db . employees . find ();
{ " _id " : " employee1 ", " id " :  1 , " name " : " zhangsan ", "
 birth " : " 1990 - 01 - 01 ", " addr " : " No .  969 ,  wenyixi   Rd
 ,  yuhang ,  hangzhou " }
{ " _id " : " employee2 ", " id " :  2 , " name " : " lisi ", " birth
 " : " 1991 - 01 - 01 ", " addr " : " No .  556 ,  xixi   Rd ,  xihu
 ,  hangzhou " }
```

```
{ " _id " : " employee3 ", " id " :  3 , " name " : " wangwu ", "
 birth " : " 1992 - 01 - 01 ", " addr " : " No .  699   wangshang   Rd
 ,  binjiang ,  hangzhou " }
```

### Spark

**In this example, we write data to a MongoDB database using Spark instead of MapReduce.**

```
package   com . aliyun . emr ;

import   com . mongodb . BasicDBObj  ect ;
import   com . mongodb . hadoop . MongoOutpu  tFormat ;
import   java . util . concurrent . atomic . AtomicInte  ger ;
import   org . apache . hadoop . conf . Configurat  ion ;
import   org . apache . spark . SparkConte  xt ;
import   org . apache . spark . api . java . JavaPairRD  D ;
import   org . apache . spark . api . java . JavaRDD ;
import   org . apache . spark . api . java . function . Function ;
import   org . apache . spark . sql . Row ;
import   org . apache . spark . sql . SparkSessi  on ;
import   org . bson . BSONObject ;
import   scala . Tuple2 ;

public   class   Test  {

  public   static   void   main ( String []  args ) {

    SparkSessi  on   ss  =  new   SparkSessi  on ( new   SparkConte
xt ());

    final   AtomicInte  ger   employeeNo  =  new   AtomicInte  ger (
0 );
    JavaRDD < Tuple2 < Object ,  BSONObject >>  javaRDD  =
        ss . read (). text (" hdfs :// emr - header - 1 : 9000 /
mongo - hadoop / employees . txt ")
          . javaRDD (). map (( Function < Row ,  Tuple2 < Object ,
BSONObject >>)  row  -> {
         BSONObject   bson  =  BasicDBObj  ect . parse ( row .
mkString ());
          return   new   Tuple2 <>(" employee " +  employeeNo .
getAndAdd ( 1 ),  bson );
       });

    JavaPairRD  D < Object ,  BSONObject >  documents  =  JavaPairRD
D . fromJavaRD  D ( javaRDD );

    Configurat  ion   outputConf  ig  =  new   Configurat  ion ();
    outputConf  ig . set (" mongo . output . uri ", " mongodb ://<
your_usern  ame >:< your_passw  ord >@ dds - xxxxxxxxxx  xxxxxxxxxx
x . mongodb . rds . aliyuncs . com : 3717 / company . employees ?
authSource = admin ");

   //  It   is   saved   as   a  " Hadoop   file ."  Actually ,  the
  data   is   written   into   the   MongoDB   database   through
the   MongoOutpu  tFormat   class .
    documents . saveAsNewA  PIHadoopFi  le (
       " file :/// this - is - completely - unused ",
        Object . class ,
        BSONObject . class ,
        MongoOutpu  tFormat . class ,
        outputConf  ig
```

```
    );
  }
}
```

Package the code into a JAR file named `spark-test.jar`. Run the following command to write data.

```
spark-submit --master yarn --class com.aliyun.emr.
Test spark-test.jar
```

After the writing has finished, you can use the MongoDB client to view the results.

### Hive

This example describes how to use Hive to read and write data in MongoDB databases through SQL statements.

First, run the `hive` command to enter CLI mode and create a table:

```
CREATE DATABASE IF NOT EXISTS company;
```

You need to create an external table that is stored in a MongoDB database. Before you do that, create a MongoDB collection named employees as described in the Preparation section.

Go back to CLI mode, execute the following SQL statements to create an external table. Connection to MongoDB is set through the TBLPROPERTIES clause.

```
CREATE EXTERNAL TABLE IF NOT EXISTS employees (
  id BIGINT,
  name STRING,
  birth STRING,
  addr STRING
)
STORED BY 'com.mongodb.hadoop.hive.MongoStorageHandler
'
WITH SERDEPROPERTIES ('mongo.columns.mapping'='{"id":"
_id"}')
TBLPROPERTIES ('mongo.uri'='mongodb://<your_username:<
your_password@dds-xxxxxxxxxx.xxxxxxxxxx.mongodb.rds.
aliyuncs.com:3717/company.employees?authSource=admin');
```

**Notice:**

Values of the `id` column in Hive are mapped to values of the `_id` column in MongoDB through SERDEPROPERTIES. You can map column values as needed. Note that the data type of the birth column is set to STRING. The reason is that Hive and MongoDB handle DATE format differently. After Hive sends data in DATE format to MongoDB, NULL may be returned when the data is queried in Hive.

**Insert some data into the table:**

```
INSERT  INTO  TABLE  employees  VALUES  ( 1 , " zhangsan ", "
1990 - 01 - 01 "," No .  969 ,  wenyixi  Rd ,  yuhang ,  hangzhou
");
INSERT  INTO  TABLE  employees  VALUES  ( 2 , " lisi ", " 1991 -
01 - 01 ", " No .  556 ,  xixi  Rd ,  xihu ,  hangzhou ");
INSERT  INTO  TABLE  employees  VALUES  ( 3 , " wangwu ", " 1992
- 01 - 01 ", " No .  699  wangshang  Rd ,  binjiang ,  hangzhou ");
```

**Execute the following statement to see the results:**

```
SELECT  *  FROM  employees  LIMIT  100 ;
OK
1     zhangsan     1990 - 01 - 01     No .  969 ,  wenyixi  Rd ,
yuhang ,  hangzhou
2     lisi     1991 - 01 - 01     No .  556 ,  xixi  Rd ,  xihu
,  hangzhou
3     wangwu     1992 - 01 - 01     No .  699  wangshang  Rd ,
binjiang ,  hangzhou
```

# 6 Deep learning with Analytics Zoo on E-MapReduce

This topic describes how to use Analytics Zoo to develop deep learning applications on Alibaba Cloud E-MapReduce.

## Introduction

Analytics Zoo is an analytics and AI platform that unites Apache Spark and Intel BigDL into an integrated pipeline. It helps users develop deep learning applications based on big data and end-to-end pipelines.

## System requirements

- JDK 8
- Spark cluster (Spark 2.x supported by EMR is recommended)
- Python 2.7(also Python 3.5 or Python 3.6), pip

## Installation of Analytics Zoo

- The latest release of Analytics Zoo is 0.2.0.
- Installation for Scala users
  - Download the pre-build version.

    You can download the Pre-build version from the Analytics Zoo page on GitHub.
  - Build Analytics Zoo using the make-dist.sh script.

    Install Apache Maven and set the environment variable MAVEN_OPTS as follows:

    ```
    export   MAVEN_OPTS ="- Xmx2g  - XX : ReservedCo  deCacheSiz  e =
    512m "
    ```

    If you use ECS instances to compile code, we recommend that you modify the mirror of the Maven repository.

    ```
    < mirror >
        < id > nexus - aliyun </ id >
        < mirrorOf > central </ mirrorOf >
        < name > Nexus   aliyun </ name >
        < url > http :// maven . aliyun . com / nexus / content /
     groups / public </ url >
    ```

```
</ mirror >
```

Download an Analytics Zoo release. Extract the file, move to the corresponding directory, and run the following command:

```
bash   make - dist . sh
```

After building Analytics Zoo, you can find a dist directory, which contains all the needed files to run an Analytics Zoo program. Use the following command to copy the files in the dist directory to the directory of the EMR software stack:

```
cp  - r   dist / / usr / lib / analytics_  zoo
```

- Installation for Python users

  Analytics Zoo can be installed either with pip or without pip. When you install Analytics Zoo with pip, PySpark and BigDL are installed. This may cause a software conflict because PySpark has already been installed on the EMR cluster. To avoid such conflicts, install Analytics Zoo without pip.

  - Installation without pip

    First, you need to run the following command:

    ```
    bash   make - dist . sh
    ```

    Change to the pyzoo directory and install Analytics Zoo:

    ```
    python   setup . py   install
    ```

- Setting environment variables

  After building Analytics Zoo, copy the dist directory to the directory of the EMR software stack and set the environment variable. Add the following lines to the */ etc / profile . d / analytics_ zoo . sh* file.

  ```
  export   ANALYTICS_  ZOO_HOME =/ usr / lib / analytics_  zoo
  export   PATH =$ ANALYTICS_  ZOO_HOME / bin :$ PATH
  ```

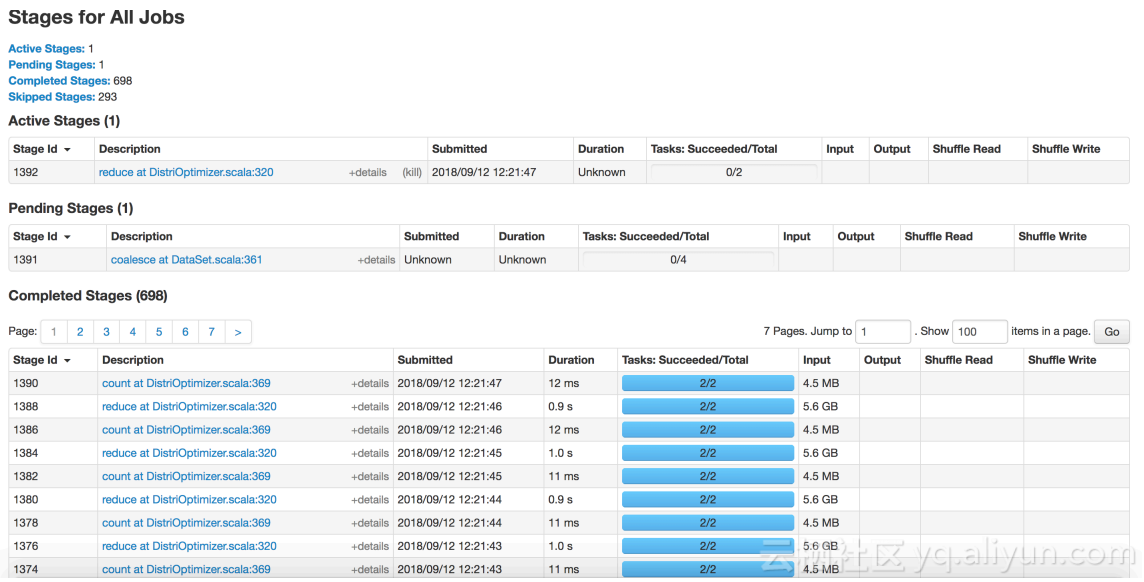
  You do not need to set SPARK_HOME because it has already been set on EMR.

## Using Analytics Zoo

- Use Spark to train and test deep learning models.
  - Use Analytics Zoo to do text classification. You can find the code and description on GitHub. Download the required data as required. Submit the following commands:

```
spark-submit --master yarn \
--deploy-mode cluster --driver-memory 8g \
--executor-memory 20g --class com.intel.analytics.
zoo.examples.textclassification.TextClassification \
/usr/lib/analytics_zoo/lib/analytics-zoo-bigdl_0.
6.0-spark_2.1.0-0.2.0-jar-with-dependencies
.jar --baseDir /news
```

  - You can log on to the instance of the Spark cluster through ssh proxy to view the status of the jobs.




You can also view the accuracy of each epoch through logs.

```
INFO optim.DistriOpti mizer$: [Epoch 2 9600/15107]
[Iteration 194][Wall Clock 193.266637037s] Trained
128 records in 0.958591653 seconds. Throughput is
133.52922 records/second. Loss is 0.74216986.
INFO optim.DistriOpti mizer$: [Epoch 2 9728/15107]
[Iteration 195][Wall Clock 194.224064816s] Trained
128 records in 0.957427779 seconds. Throughput is
133.69154 records/second. Loss is 0.51025534.
INFO optim.DistriOpti mizer$: [Epoch 2 9856/15107]
[Iteration 196][Wall Clock 195.189488678s] Trained
128 records in 0.965423862 seconds. Throughput is
132.58424 records/second. Loss is 0.553785.
INFO optim.DistriOpti mizer$: [Epoch 2 9984/15107]
[Iteration 197][Wall Clock 196.164318688s] Trained
```

```
128   records   in   0 . 97483001   seconds .  Throughput   is
131 . 30495   records / second .  Loss   is   0 . 5517549 .
```

- Use PySpark and Jupyter to train deep learning models on Analytics Zoo.
  - Install Jupyter.

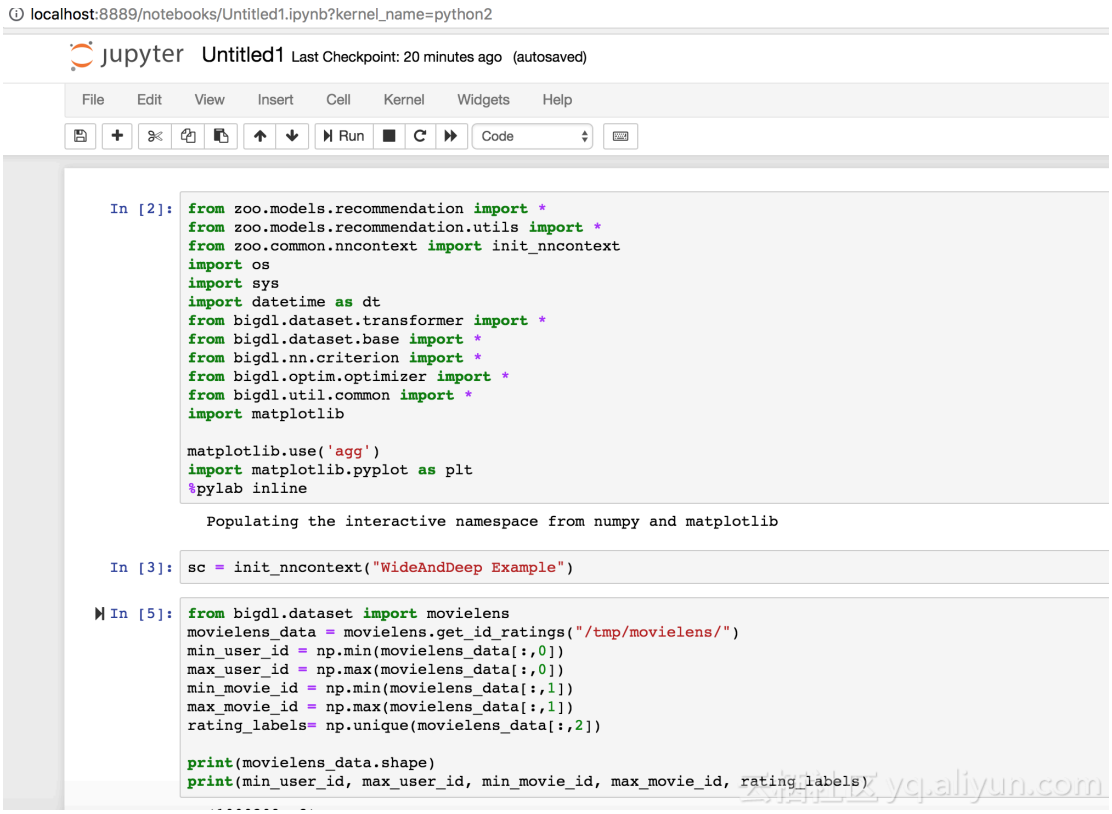
    ```
    pip   install   jupyter
    ```

  - Run the following command to start Jupyter.

    ```
    jupyter - with - zoo . sh
    ```

  - We recommend that you use the pre-defined Wide And Deep Learning models provided by Analytics Zoo, for more information please refer to GitHub.

    1. Import data.




    2. Build a model and create an optimizer.

```
In [10]: wide_n_deep = WideAndDeep(5, column_info, "wide_n_deep")
```

```
creating: createZooWideAndDeep
```

```
In [11]: # Create an Optimizer
batch_size = 8000

optimizer = Optimizer(
    model=wide_n_deep,
    training_rdd=train_data,
    criterion=ClassNLLCriterion(),
    optim_method=Adam(learningrate = 0.001, learningrate_decay=0.00005),
    end_trigger=MaxEpoch(10),
    batch_size=batch_size)

# Set the validation logic
optimizer.set_validation(
    batch_size=batch_size,
    val_rdd=test_data,
    trigger=EveryEpoch(),
    val_method=[Top1Accuracy(), Loss(ClassNLLCriterion())]
)
log_dir='/tmp/bigdl_summaries/'
app_name='wide_n_deep-'+dt.datetime.now().strftime("%Y%m%d-%H%M%S")
train_summary = TrainSummary(log_dir=log_dir,
                                        app_name=app_name)
val_summary = ValidationSummary(log_dir=log_dir,
                                      app_name=app_name)
optimizer.set_train_summary(train_summary)
optimizer.set_val_summary(val_summary)
print("saving logs to %s" % (log_dir + app_name))
```



## 3. Start the training process.

```
In [12]: %%time
# Boot training process
optimizer.optimize()
print("Optimization Done.")
```

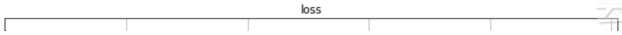
```
Optimization Done.
CPU times: user 85.9 ms, sys: 16.7 ms, total: 103 ms
Wall time: 2min 52s
```

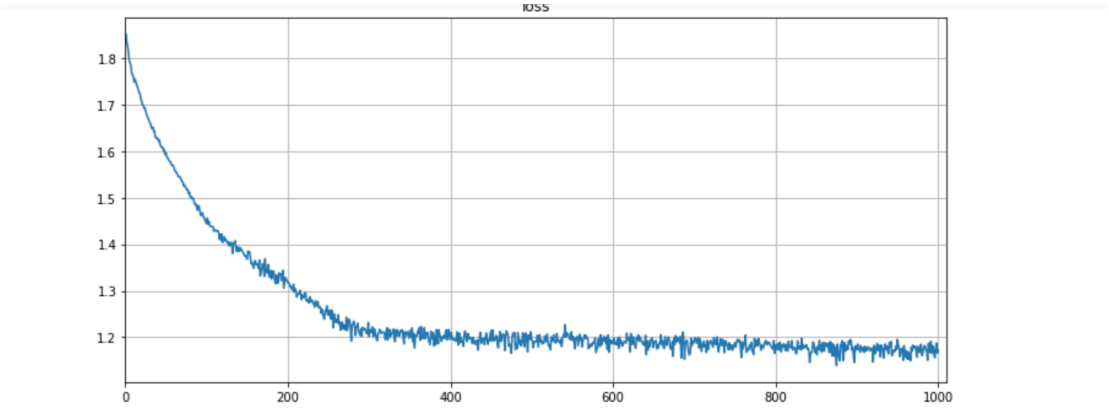


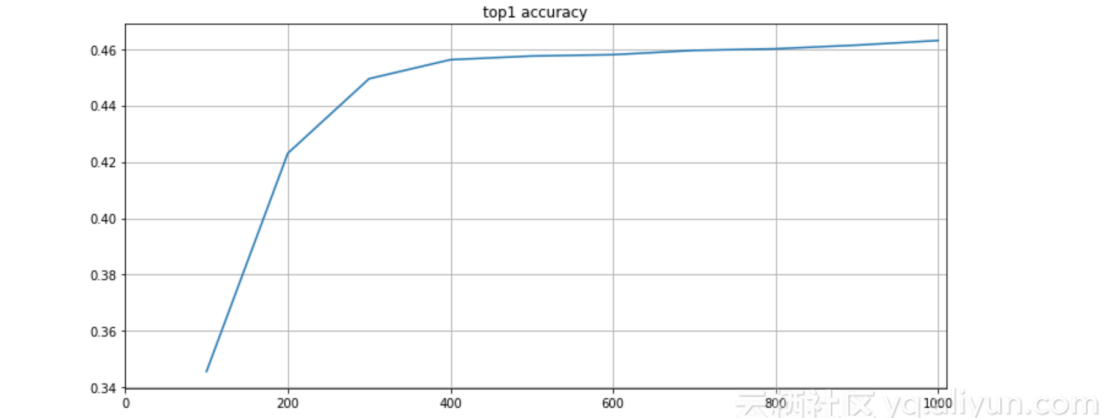
## 4. View training results.

```
In [16]: loss = np.array(train_summary.read_scalar("Loss"))
top1 = np.array(val_summary.read_scalar("Top1Accuracy"))

plt.figure(figsize = (12,12))
plt.subplot(2,1,1)
plt.plot(loss[:,0],loss[:,1],label='loss')
plt.xlim(0,loss.shape[0]+10)
plt.grid(True)
plt.title("loss")
plt.subplot(2,1,2)
plt.plot(top1[:,0],top1[:,1],label='top1')
plt.xlim(0,loss.shape[0]+10)
plt.title("top1 accuracy")
plt.grid(True)
```





# 7 Adaptive execution of Spark SQL

Spark SQL of Alibaba Cloud Elastic MapReduce (E-MapReduce) 3.13.0 supports adaptive execution. It is used to set the number of reduce tasks automatically, solve data skew, and dynamically optimize execution plans.

## Solved problems

Adaptive execution of Spark SQL solves the following problems:

- The number of shuffle partitions

  Currently, the number of tasks in the reduce stage in Spark SQL depends on the value of the `spark.sql.shuffle.partition` parameter (the default value is 200). Once this parameter has been specified for a job, the number of reduce tasks in all stages is the same value when the job is running.

  For different jobs, and for different reduce stages of one job, the actual data size can be quite different. For example, data to be processed in the reduce stage may have a size of 10 MB or 100 GB. If the parameter is specified using the same value, it has a significant impact on the actual processing efficiency. For example, 10 MB of data can be processed using only one task. If the value of the `spark.sql.shuffle.partition` parameter is set to the default value of 200, then 10 MB of data is partitioned to be processed by 200 tasks. This increases scheduling overheads and lowers processing efficiency.

  By setting the range of the shuffle partition number, the adaptive execution framework of Spark SQL can dynamically adjust the number of reduce tasks in the range for different stages of different jobs.

  This significantly reduces the costs for optimization (no need to find a fixed value ). Additionally, the numbers of reduce tasks in different stages of one job can be dynamically adjusted.

  Parameter:

| Attribute | Default value | Description |
| --- | --- | --- |
| spark.sql.adaptive.enabled | false | Enables or disables adaptive execution. |

| Attribute | Default value | Description |
| --- | --- | --- |
| spark.sql.adaptive.minNumPostShufflePartitions | 1 | The minimum number of reduce tasks. |
| spark.sql.adaptive.maxNumPostShufflePartitions | 500 | The maximum number of the reduce tasks. |
| spark.sql.adaptive.shuffle.targetPostShuffleInputSize | 67108864 | Dynamically adjusts the number of reduce tasks based on the partition size. For example, if the value is set to 64 MB, then each task in the reduce stage processes more than 64 MB data. |
| spark.sql.adaptive.shuffle.targetPostShuffleRowCount | 20000000 | Dynamically adjusts the number of reduce tasks based on the row number in the partition. For example, if the value is set to 20000000, then each task in the reduce stage processes more than 20,000,000 rows of data. |

- Data skew

  Data skew is a common issue in SQL join operations. It refers to the scenario where certain tasks involve too much data in the processing, which leads to long tails. Currently, Spark SQL does not perform optimization for skewed data.

  The Adaptive Execution framework of Spark SQL can automatically detect skewed data and perform optimization for it at runtime.

  SparkSQL optimizes skewed data as follows: it splits the data that is in the skewed partition, processes the data through multiple tasks, and then combines the results through SQL union operations.

  Supported join types:

| Type | Description |
| --- | --- |
| Inner | Skewed data can be handled in both tables. |

| Type | Description |
| --- | --- |
| Cross | Skewed data can be handled in both tables. |
| LeftSemi | Skewed data can only be handled in the left table. |
| LeftAnti | Skewed data can only be handled in the left table. |
| LeftOuter | Skewed data can only be handled in the left table. |
| RightOuter | Skewed data can only be handled in the right table. |

Parameter:

| Attribute | Default value | Description |
| --- | --- | --- |
| spark.sql.adaptive.enabled | false | Enables or disables the adaptive execution framework. |
| spark.sql.adaptive.skewedJoin.enabled | false | Enables or disables the handling of skewed data. |
| spark.sql.adaptive.skewedPartitionFactor | 10 | A partition is identified as a skewed partition only when the following scenarios occur. First, the size of a partition is greater than this value (median size of all partitions) and the value of the spark.sql.adaptive.skewedPartitionSizeThreshold parameter. Second, the rows in a partition are greater than this value (median rows in all partitions) and the value of the spark.sql.adaptive.skewedPartitionSizeThreshold parameter. |

| Attribute | Default value | Description |
| --- | --- | --- |
| spark.sql.adaptive.skewedPartitionSizeThreshold | 67108864 | The size threshold for a skewed partition. |
| spark.sql.adaptive.skewedPartitionRowCountThreshold | 10000000 | The row number threshold for a skewed partition. |
| spark.shuffle.statistics.verbose | false | When the value of this parameter is true, MapStatus collects information about the number of rows in each partition for handling skewed data. |

- Execution plan optimization at runtime

  Catalyst optimizer of Spark SQL converts logical plans that are converted from SQL statements into physical execution plans and executes those physical execution plans. However, the physical execution plan produced by Catalyst may not be optimal because of lack or inaccuracy of statistics. For example, Spark SQL may choose SortMergeJoinExec instead of BroadcastJoin, while BroadcastJoin is the optimal option in the scenario.

  The Adaptive Execution framework of Spark SQL determines whether to use BroadcastJoin instead of SortMergeJoin to improve query performance based on the size of the shuffle write in the shuffle stage.

  Parameter:

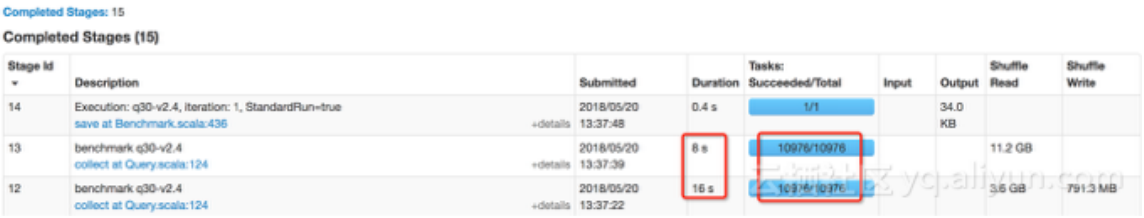
| Attribute | Default value | Description |
| --- | --- | --- |
| spark.sql.adaptive.enabled | false | Enables or disables the adaptive execution framework. |
| spark.sql.adaptive.join.enabled | true | Whether to determine a better join strategy at runtime. |
| spark.sql.adaptiveBroadcastJoinThreshold | Equals to spark.sql.autoBroadcastJoinThreshold. | Determines whether to use broadcast join to optimize join queries. |

## Test

Take some TPC-DS queries as test samples.

- Shuffle partition number
  - Query 30

    Native Spark:

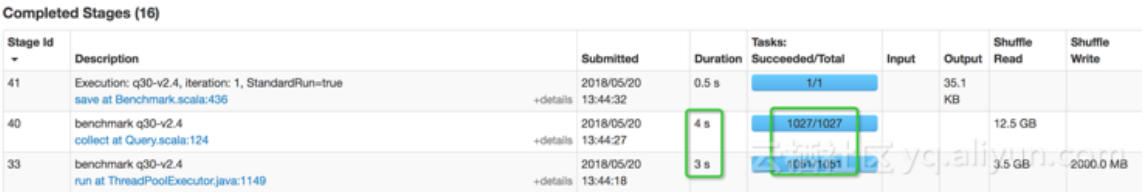


Completed Stages: 15

Completed Stages (15)

| Stage Id | Description | Submitted | Duration | Tasks: Succeeded/Total | Input | Output | Shuffle Read | Shuffle Write |
|---|---|---|---|---|---|---|---|---|
| 14 | Execution: q30-v2.4, iteration: 1, StandardRun=true<br>save at Benchmark.scala:436 +details | 2018/05/20 13:37:48 | 0.4 s | 1/1 | | 34.0 KB | | |
| 13 | benchmark q30-v2.4<br>collect at Query.scala:124 +details | 2018/05/20 13:37:39 | 8 s | 10976/10976 | | | 11.2 GB | |
| 12 | benchmark q30-v2.4<br>collect at Query.scala:124 +details | 2018/05/20 13:37:22 | 16 s | 10976/10976 | | | 3.6 GB | 791.3 MB |

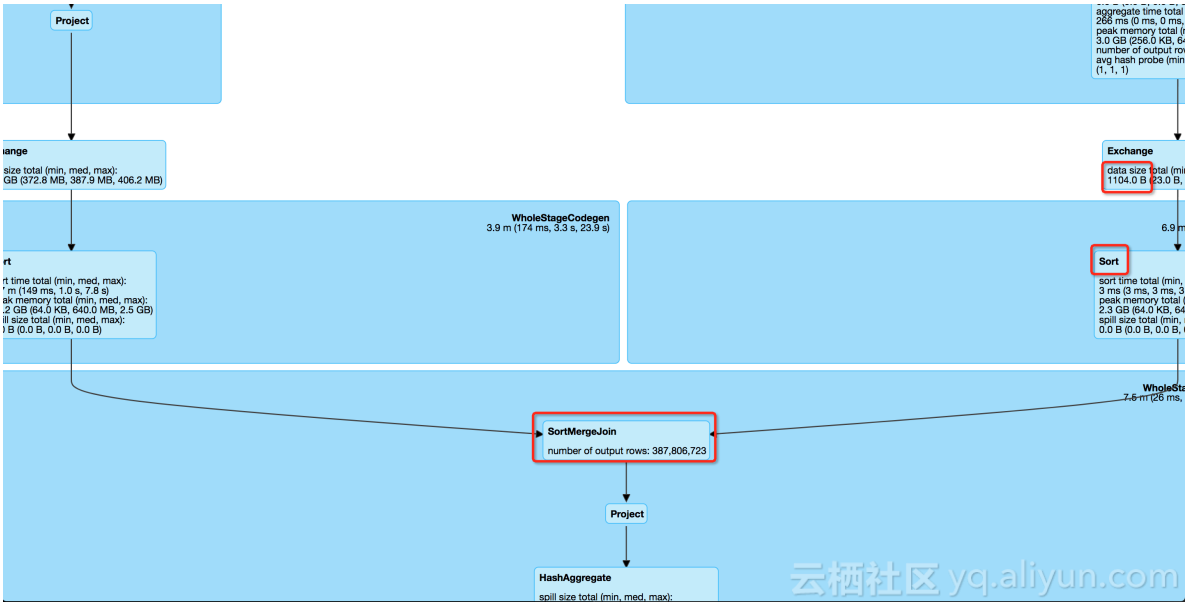
  - Adjusts the number of reduce tasks adaptively.



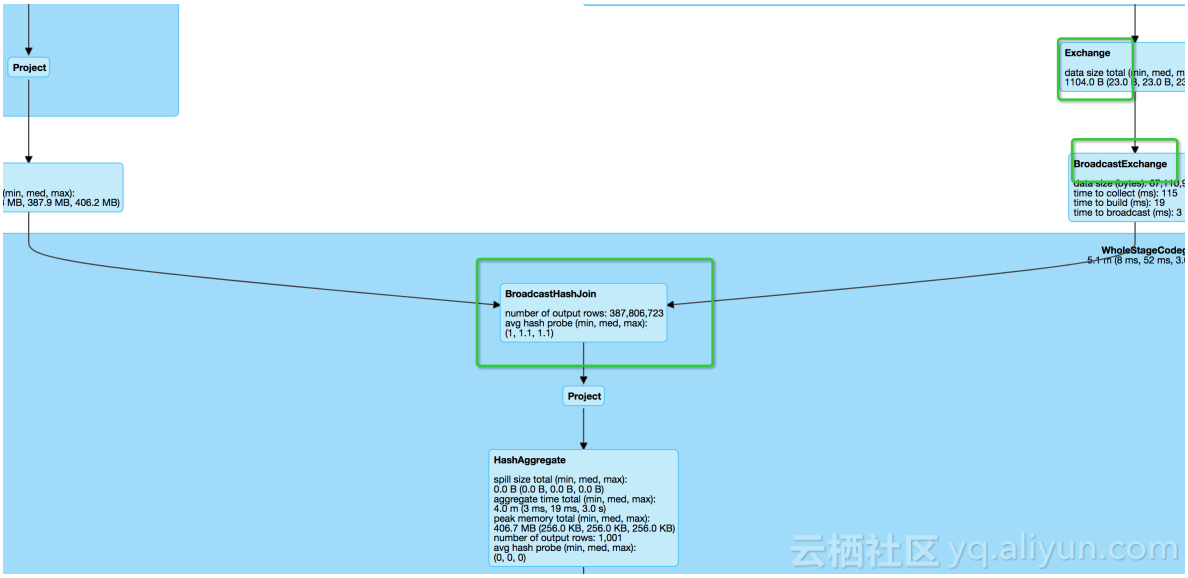
Completed Stages (16)

| Stage Id | Description | Submitted | Duration | Tasks: Succeeded/Total | Input | Output | Shuffle Read | Shuffle Write |
|---|---|---|---|---|---|---|---|---|
| 41 | Execution: q30-v2.4, iteration: 1, StandardRun=true<br>save at Benchmark.scala:436 +details | 2018/05/20 13:44:32 | 0.5 s | 1/1 | | 35.1 KB | | |
| 40 | benchmark q30-v2.4<br>collect at Query.scala:124 +details | 2018/05/20 13:44:27 | 4 s | 1027/1027 | | | 12.5 GB | |
| 33 | benchmark q30-v2.4<br>run at ThreadPoolExecutor.java:1149 +details | 2018/05/20 13:44:18 | 3 s | 1051/1051 | | | 3.5 GB | 2000.0 MB |

- Execution plan optimization at runtime (SortMergeJoin to BroadcastJoin).




Uses BroadcastJoin adaptively.



# 8 E-MapReduce data migration solution

This topic describes how to migrate data from a self-built cluster to an E-MapReduce (EMR) cluster.

Applicable migration scenarios include:

- Migrating data from an offline Hadoop cluster to E-MapReduce.
- Migrating data from a self-built Hadoop cluster on ECS to E-MapReduce.

Supported data sources include:

- HDFS incremental upstream data sources such as RDS incremental data and Flume .

Network interconnection between new and old clusters

- Self-built Hadoop cluster on an offline IDC

  A self-built Hadoop cluster can be migrated to E-MapReduce through OSS, or by using Alibaba Cloud Express Connect, to establish a connection between your offline IDC and the VPC in which your E-MapReduce cluster is located.
- Self-built Hadoop cluster on ECS instances

  Because VPC networks are logically isoloated, we recommend that you use the VPC-Connected E-MapReduce service to establish an interconnection. Depending on the specific network types involved for interconnection, you need to perform the following actions:

  - Interconnection between classic networks and VPC networks

    For a Hadoop cluster built on ECS instances, you need to interconnect the classic network and VPC network using the ECS ClassicLink method. For more information, see Build a ClassicLink connection.
  - Interconnection between VPC networks

    To ensure optimal connectivity between VPC networks, we recommned that you create the new cluster in the same region and zone as the old cluster.

### HDFS data migration

- Synchronize data with DistCp

  For more information, see Hadoop DistCp.

  You can migrate full and incremental HDFS data using the DistCp tool. To alleviate pressures on your current cluster resources, we recommend that you execute the `distcp` command after the new and old cluster networks are interconnected.

  - Full data synchronization

    ```
    hadoop distcp -pbugpcax -m 1000 -bandwidth 30 hdfs
    :// oldcluster ip : 8020 / user / hive / warehouse / user /
    hive / warehouse
    ```

  - Incremental data synchronization

    ```
    hadoop distcp -pbugpcax -m 1000 -bandwidth 30 -
    update -delete hdfs :// oldcluster ip : 8020 / user / hive /
    warehouse / user / hive / warehouse
    ```

  Parameter descriptions:

  - *hdfs :// oldcluster ip : 8020* indicates the namenode IP of the old cluster. If there are multiple namenodes, input the namenode that is in the active status.
  - By default, the number of replicas is 3. If you want to keep the original number of replicas, add r after -p, such as -prbugpcax. If the permissions and ACL do not need to be synchronized, remove p and a after -p.
  - -m indicates the amount of maps and the size of the cluster, which corresponds to the data volume. For example, if a cluster has a 2000-core cpu, you can specify 2000 maps.
  - -bandwidth indicates an estimated value of the synchronized speed of a single map, which is implemented by controlling the copy speed of replicas.
  - -update, verifies the checksum and file size of the source and target files. If the file sizes compared are different, the source file updates the target cluster data. If there are data writes during the synchronization of the old and new clusters, -update can be used for incremental data synchronization.
  - -delete, if data in the old cluster no longer exists, the data in the new cluster will be deleted.

   Note:

- The overall speed of migration is affected by cluster badwidth and size. The larger the number of files, the longer the checksum takes to process. If you have a large amount of data to migrate, try to synchronize several directories to evaluate the overall time. If synchronization is performed within the specified time period, you can split the directory into several small directories and synchronize them one at a time.
- A short service stop is required for the full data synchronization to enable double write and double counting, and to directly switch the service to the new cluster.

· HDFS permission configuration

HDFS provides permission settings. Before migrating HDFS data, you need to ensure whether the old cluster has an ACL rule and if the rule is to be synchronized, and check if `dfs . permission s . enabled` and `dfs . namenode . acls . enabled` were configured the same in the old and new clusters. The configurations will take effect immediately.

If there is an ACL rule to be synchronized, the distcp parameter must be added to -p to synchronize the permission parameter. If the distcp operation displays that the cluster does not support the ACL, this means that you did not set the ACL rule for the corresponding cluster. If the new cluster is not configured with the ACL rule, you can add it and restart NM. If the old cluster does not support an ACL rule, you do not need to set or synchronize an ACL rule.

### Hive metadata synchronization

- **Overview**

  **Hive metadata is generally stored in MySQL. When compared with MySQL data synchronization, note that:**

  - **The location must be changed**
  - **Hive version alignment is required**

  **E-MapReduce supports Hive metabases, including**

  - **Unified metabase, whereby EMR manages RDS and each user has a schema**
  - **Self-built RDS**
  - **Self-built MySQL on ECS instances**

  **To ensure data is consistent after migration between the old and new clusters, we recommend that you stop the metastore service during the migration, open the metastore service on the old cluster after the migration, and then submit jobs on the new cluster.**

- **Procedure:**

  1. **Delete the metabase of the new cluster and input** `drop database xxx`**.**
  2. **Run the** `mysqldump` **command to export the table structure and data of the old cluster's metabase.**
  3. **Replace the location. Tables and partitions in the Hive metadata all have location information witinh the dfs nameservices prefix, such as** *`hdfs://mycluster:8020/`***. However, the nameservices prefix of an E-**

MapReduce cluster is emr-cluster, which means you need to replace the location information.

To replace the location information, export the data as follows.

```
mysqldump -- databases hivemeta -- single - transactio n -
u root - p > hive_datab ases . sql
```

Use sed to replace *hdfs :// oldcluster : 8020 /* with *hdfs :// emr - cluster /* and then import data into the new database.

```
mysql hivemeta - p < hive_datab ases . sql
```

4. n the interface of the new cluster, stop the hivemetastore service.
5. Log on to the new metabase and create a database.
6. In the new metabase, import all data exported from the old metabase after the location field is replaced.
7. Currently, E-MapReduce Hive version is the latest stable version. However, if the Hive version of your self-built cluster is earlier, any imported data may not be directly usable. To resolve this issue, you need to execute the upgraded Hive script (ignore table and field problems). For more information, see Hive upgrade scripts. For example, to upgrade Hive 1.2 to 2.3.0, execute `upgrade - 1 . 2 . 0 - to - 2 . 0 . 0 . mysql . sql , upgrade - 2 . 0 . 0 - to - 2 . 1 . 0 . mysql . sql , upgrade - 2 . 1 . 0 - to - 2 . 2 . 0 . mysql . sql` , and `upgrade - 2 . 2 . 0 - to - 2 . 3 . 0 . mysql . sql` in sequence. This script is mainly used to build the table, add the field, and change the content.
8. Exceptions that the table and the field already exist can be ignored. After all metadata are revised, restart MetaServer, input the `hive` command in the command line, query the database and table, and verify the information is correct.

### Flume data migration

- Flume simultaneous write in two clusters configuration

  Enable the Flume service in the new cluster and write the data to the new cluster in accordance with the rules that are identical to the old cluster.

- Write the Flume partition table

  When executing the Flume data double-write, you must control the start timing to make sure that the new cluster is synchronized when Flume starts a new time partition. If Flume synchronizes all the tables every hour, you need to enable the Flume synchronization service before the next synchronization. This ensures that the data written by Flume in the new hour is properly duplicated. Incomplete old data is then synchronized when full data synchronization with DistCp is performed . The new data generated after the simultaneous write time is enabled is not synchronized.

   Note:
  When you partition data, do NOT put the new written data into the data synchronization directory.

Job synchronization

If the verion upgrades of Hadoop, Hive, Spark, and MapReduce are large, you may rebuild your jobs on demand.

Common issues and corresponding solutions are as follows:

- Gateway OOM

  Change `/ etc / ecm / hive - conf / hive - env . sh .`

  `export HADOOP_HEA PSIZE = 512` is changed to 1024.

- Insufficient job execution memory

  `mapreduce.map.java.opts` adjusts the startup parameters passed to the virtual machine when the JVM virtual machine is started. The default value -Xmx200m indicates the maximum amount of heap memory used by this Java program. When the amount is exceeded, the JVM displays the Out of Memory exception

  ```
  and terminates the set mapreduce . map . java . opts =-
  Xmx3072m process .
  ```

  mapreduce.map.memory.mb sets the memory limit of the Container, which is read and controlled by NodeManager. When the memory size of the Container exceeds this parameter value, NodeManager will kill the Container.

  ```
  set mapreduce . map . memory . mb = 3840
  ```

### Data verification

Data is verified through a customer's self-generated reports.

### Presto cluster migration

If a Presto cluster is used for data queries, the Hive configuration files need to be modified. For more information, see Presto documentation.

The Hive properties that need to be modified are as follows:

- connector . name = hive - hadoop2
- hive . metastore . uri = thrift :// emr - header - 1 . cluster - 500148414 : 9083
- hive . config . resources =/ etc / ecm / hadoop - conf / core - site . xml , / etc / ecm / hadoop - conf / hdfs - site . xml
- hive . allow - drop - table = true
- hive . allow - rename - table = true
- hive . recursive - directorie s = true

### Appendix

Alignment example of upgrading Hive version 1.2 to 2.3:

```
source  / usr / lib / hive - current / scripts / metastore / upgrade
/ mysql / upgrade - 1 . 2 . 0 - to - 2 . 0 . 0 . mysql . sql
CREATE   TABLE   COMPACTION  _QUEUE  (
  CQ_ID   bigint   PRIMARY   KEY ,
  CQ_DATABAS  E   varchar ( 128 )  NOT   NULL ,
  CQ_TABLE   varchar ( 128 )  NOT   NULL ,
  CQ_PARTITI  ON   varchar ( 767 ),
  CQ_STATE   char ( 1 )  NOT   NULL ,
  CQ_TYPE   char ( 1 )  NOT   NULL ,
  CQ_WORKER_  ID   varchar ( 128 ),
  Cq_start   bigint ,
  CQ_RUN_AS   varchar ( 128 ),
  CQ_HIGHEST  _TXN_ID   bigint ,
  CQ_META_IN  FO   varbinary ( 2048 ),
  CQ_HADOOP_  JOB_ID   varchar ( 32 )
)  ENGINE = InnoDB   DEFAULT   CHARSET = latin1 ;
CREATE   TABLE   TXNS  (
  TXN_ID   bigint   PRIMARY   KEY ,
  TXN_STATE   char ( 1 )  NOT   NULL ,
  TXN_STARTE  D   bigint   NOT   NULL ,
  TXN_LAST_H  EARTBEAT   bigint   NOT   NULL ,
  TXN_USER   varchar ( 128 )  NOT   NULL ,
  TXN_HOST   varchar ( 128 )  NOT   NULL ,
  TXN_AGENT_  INFO   varchar ( 128 ),
  TXN_META_I  NFO   varchar ( 128 ),
  TXN_HEARTB  EAT_COUNT   int
)  ENGINE = InnoDB   DEFAULT   CHARSET = latin1 ;
CREATE   TABLE   HIVE_LOCKS  (
```

```
   HL_LOCK_EX  T_ID   bigint   NOT   NULL ,
   HL_LOCK_IN  T_ID   bigint   NOT   NULL ,
   HL_TXNID   bigint ,
   HL_DB   varchar ( 128 )  NOT   NULL ,
   HL_TABLE   varchar ( 128 ),
   HL_PARTITI  ON   varchar ( 767 ),
   HL_LOCK_ST  ATE   char ( 1 )  not   null ,
   HL_LOCK_TY  PE   char ( 1 )  not   null ,
   HL_LAST_HE  ARTBEAT   bigint   NOT   NULL ,
   HL_ACQUIRE  D_AT   bigint ,
   HL_USER   varchar ( 128 )  NOT   NULL ,
   HL_HOST   varchar ( 128 )  NOT   NULL ,
   HL_HEARTBE  AT_COUNT   int ,
   HL_AGENT_I  NFO   varchar ( 128 ),
   HL_BLOCKED  BY_EXT_ID   bigint ,
   HL_BLOCKED  BY_INT_ID   bigint ,
   PRIMARY   KEY ( HL_LOCK_EX  T_ID ,  HL_LOCK_IN  T_ID ),
   KEY   HIVE_LOCK_  TXNID_INDE  X  ( HL_TXNID )
)  ENGINE = InnoDB   DEFAULT   CHARSET = latin1 ;
 CREATE   INDEX   HL_TXNID_I  DX   ON   HIVE_LOCKS  ( HL_TXNID );
 source  / usr / lib / hive - current / scripts / metastore / upgrade
 / mysql / upgrade - 1 . 2 . 0 - to - 2 . 0 . 0 . mysql . sql
 source  / usr / lib / hive - current / scripts / metastore / upgrade
 / mysql / upgrade - 2 . 0 . 0 - to - 2 . 1 . 0 . mysql . sql

 CREATE   TABLE   TXN_COMPON  ENTS  (
   TC_TXNID   bigint ,
   TC_DATABAS  E   varchar ( 128 )  NOT   NULL ,
   TC_TABLE   varchar ( 128 ),
   TC_PARTITI  ON   varchar ( 767 ),
   FOREIGN   KEY  ( TC_TXNID )  REFERENCES   TXNS  ( TXN_ID )
)  ENGINE = InnoDB   DEFAULT   CHARSET = latin1 ;
 source  / usr / lib / hive - current / scripts / metastore / upgrade
 / mysql / upgrade - 2 . 0 . 0 - to - 2 . 1 . 0 . mysql . sql
 source  / usr / lib / hive - current / scripts / metastore / upgrade
 / mysql / upgrade - 2 . 1 . 0 - to - 2 . 2 . 0 . mysql . sql
 CREATE   TABLE   IF   NOT   EXISTS  ` NOTIFICATI  ON_LOG `
(
    ` NL_ID `  BIGINT ( 20 )  NOT   NULL ,
    ` EVENT_ID `  BIGINT ( 20 )  NOT   NULL ,
    ` EVENT_TIME `  INT ( 11 )  NOT   NULL ,
    ` EVENT_TYPE `  varchar ( 32 )  NOT   NULL ,
    ` DB_NAME `  varchar ( 128 ),
    ` TBL_NAME `  varchar ( 128 ),
    ` MESSAGE `  mediumtext ,
     PRIMARY   KEY  (` NL_ID `)
)  ENGINE = InnoDB   DEFAULT   CHARSET = latin1 ;
 CREATE   TABLE   IF   NOT   EXISTS  ` PARTITION_  EVENTS ` (
  ` PART_NAME_  ID `  bigint ( 20 )  NOT   NULL ,
  ` DB_NAME `  varchar ( 128 )  CHARACTER   SET   latin1   COLLATE
 latin1_bin   DEFAULT   NULL ,
  ` EVENT_TIME `  bigint ( 20 )  NOT   NULL ,
  ` EVENT_TYPE `  int ( 11 )  NOT   NULL ,
  ` PARTITION_  NAME `  varchar ( 767 )  CHARACTER   SET   latin1
 COLLATE   latin1_bin   DEFAULT   NULL ,
  ` TBL_NAME `  varchar ( 128 )  CHARACTER   SET   latin1   COLLATE
 latin1_bin   DEFAULT   NULL ,
   PRIMARY   KEY  (` PART_NAME_  ID `),
   KEY  ` PARTITIONE  VENTINDEX ` (` PARTITION_  NAME `)
)  ENGINE = InnoDB   DEFAULT   CHARSET = latin1 ;

 CREATE   TABLE   COMPLETED_  TXN_COMPON  ENTS  (
   CTC_TXNID   bigint   NOT   NULL ,
   CTC_DATABA  SE   varchar ( 128 )  NOT   NULL ,
```

```
   CTC_TABLE   varchar ( 128 ),
   CTC_PARTIT  ION   varchar ( 767 )
)  ENGINE = InnoDB   DEFAULT   CHARSET = latin1 ;
  source  / usr / lib / hive - current / scripts / metastore / upgrade
 / mysql / upgrade - 2 . 1 . 0 - to - 2 . 2 . 0 . mysql . sql
  source  / usr / lib / hive - current / scripts / metastore / upgrade
 / mysql / upgrade - 2 . 2 . 0 - to - 2 . 3 . 0 . mysql . sql
   CREATE   TABLE   NEXT_TXN_I  D  (
   NTXN_NEXT   bigint   NOT   NULL
)  ENGINE = InnoDB   DEFAULT   CHARSET = latin1 ;
 INSERT   INTO   NEXT_TXN_I  D   VALUES ( 1 );
 CREATE   TABLE   NEXT_LOCK_  ID  (
   NL_NEXT   bigint   NOT   NULL
)  ENGINE = InnoDB   DEFAULT   CHARSET = latin1 ;
 INSERT   INTO   NEXT_LOCK_  ID   VALUES ( 1 );
```

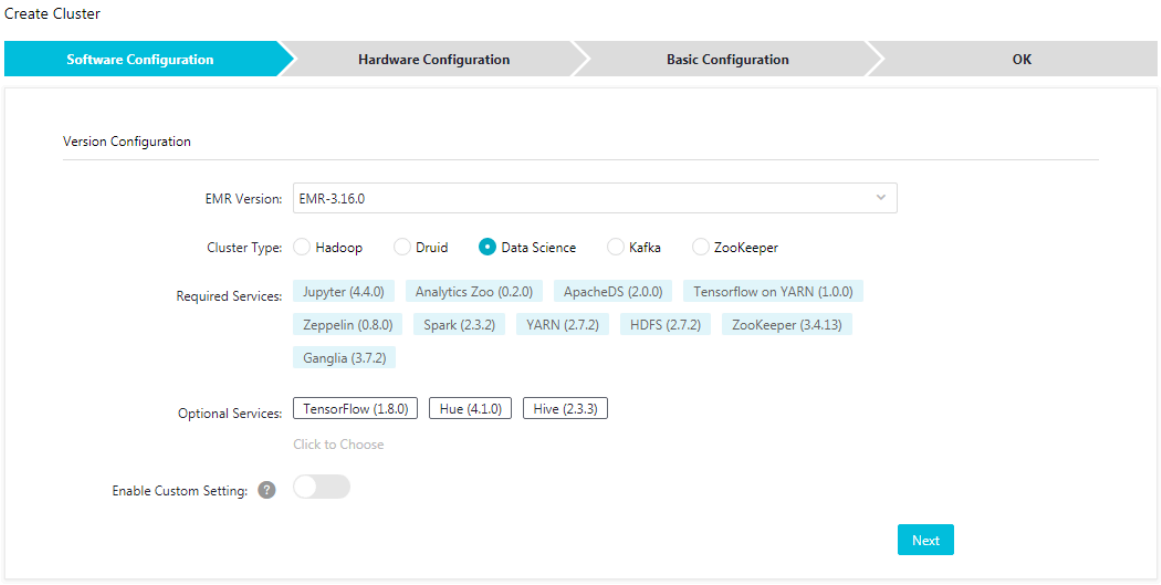
# 9 Use EMR Data Science clusters for deep learning

**Data Science cluster is a new model available in E-MapReduce (EMR) 3.13.0 and later versions for machine learning and deep learning. You can use GPU or CPU models to perform data training through Data Science clusters. Training data can be stored on HDFS and OSS. EMR supports TensorFlow for distributed training on large amounts of data.**

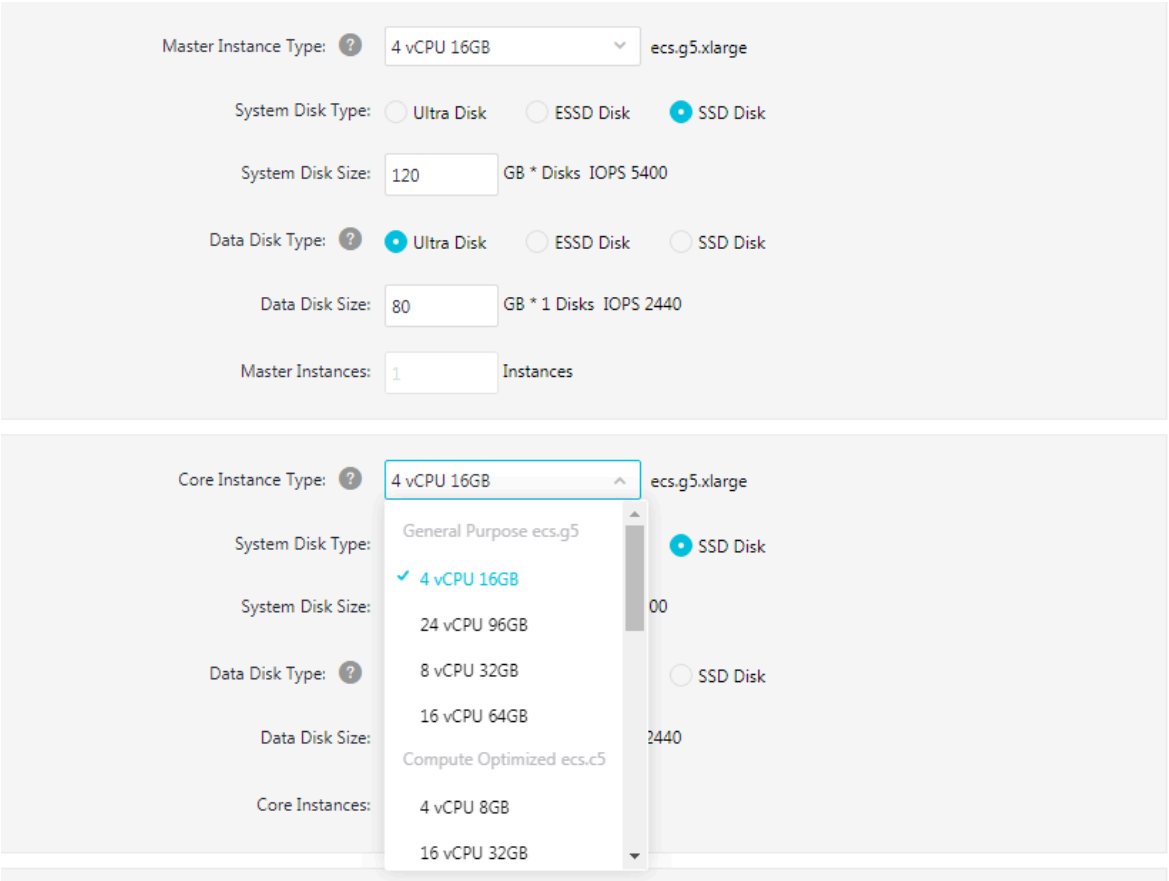
## Create cluster

- **Prerequisites for creating an EMR Data Science cluster:**
  - **EMR 3.13.0 or later.**
  - **Data Science as the cluster type.**

- Create a cluster




Select a CPU model for Master Instance Type, and select a CPU or GPU model for Core Instance Type.




If you select a GPU model, EMR provides Nvidia GPU drivers and the corresponding Cudnn installation.

After the cluster is created, the corresponding service, driver, and Cudnn are installed. The docker service is installed on all core nodes.

### Run TensorFlow on a Data Science cluster

- TensorFlow

  TensorFlow is an open-srouce machine learning framework for deep learning of machine learning tasks and training neural models. For more information about TensorFlow, see TensorFlow.

- TensorFlow on YARN

  TensorFlow on YARN developed by the EMR kernel team is a distributed TensorFlow framework based on YARN scheduling. It supports running TensorFlow jobs on YARN and using GPU for training. For information about how to use TensorFlow on YARN, see TensorFlow instructions.

- Use TensorFlow on YARN to perform deep learning

  TensorFlow on YARN can use high-level APIs for training with more concise codes. This topic takes the Wide and Deep model as an example for training. For information about more models, see github. Click here to download training data. Data for training is adult.data and adult.test. This example writes training steps in Python according to the stand-alone version.

  1. Define training data, and then upload training data and validation data to HDFS.

     Put the training data to the /ml/ directory of hdfs:

     ```
     hdfs dfs -put adut.data adult.test /ml/
     ```

  2. Specify the training data path in the training code:

     ```
     TRAIN_FILES = ['hdfs://emr-header-1.cluster-500157403:9000/ml/adult.data']
     EVAL_FILES = ['hdfs://emr-header-1.cluster-500157403:9000/ml/adult.test']
     ```

     HDFS schema is set according to your cluster. If the cluster is not a high availability cluster (HA cluster), you only need to check the `fs.defaultFS`

property in *core-site.xml*. If the cluster is an HA cluster, by default, the HDFS schema is *emr-cluster*.

3. Define feature columns.

   Define the corresponding features according to the wide and deep model:

```
""" Build a wide and deep model for predicting
 income category .
"""
( gender , race , education , marital_st atus , relationsh
 ip ,
 workclass , occupation , native_cou ntry , age ,
 education_ num , capital_ga in , capital_lo ss ,
 hours_per_ week ) = INPUT_COLU MNS
# Continuous columns can be converted to categorica
 l via bucketizat ion
 age_bucket s = tf . feature_co lumn . bucketized _column (
 age , boundaries =[ 18 , 25 , 30 , 35 , 40 , 45 , 50 , 55
 , 60 , 65 ])
# Wide columns and deep columns .
 wide_colum ns = [
# Interactio ns between different categorica l features
   can also
# be added as new virtual features .
 tf . feature_co lumn . crossed_co lumn (
[' education ', ' occupation '], hash_bucke t_size = int ( 1e4
 )),
 tf . feature_co lumn . crossed_co lumn (
[ age_bucket s , race , ' occupation '], hash_bucke t_size =
 int ( 1e6 )),
 tf . feature_co lumn . crossed_co lumn (
[' native_cou ntry ', ' occupation '], hash_bucke t_size = int
 ( 1e4 )),
 gender ,
 native_cou ntry ,
 education ,
 occupation ,
 workclass ,
 marital_st atus ,
 relationsh ip ,
 age_bucket s ,
]
 deep_colum ns = [
# Use indicator columns for low dimensiona l
 vocabulari es
 tf . feature_co lumn . indicator_ column ( workclass ),
 tf . feature_co lumn . indicator_ column ( education ),
 tf . feature_co lumn . indicator_ column ( marital_st atus ),
 tf . feature_co lumn . indicator_ column ( gender ),
 tf . feature_co lumn . indicator_ column ( relationsh ip ),
 tf . feature_co lumn . indicator_ column ( race ),
# Use embedding columns for high dimensiona l
 vocabulari es
 tf . feature_co lumn . embedding_ column (
 native_cou ntry , dimension = embedding_ size ),
 tf . feature_co lumn . embedding_ column ( occupation ,
 dimension = embedding_ size ),
 age ,
 education_ num ,
 capital_ga in ,
 capital_lo ss ,
```

```
 hours_per_  week ,
]
```

4. **Define input_fn.**

   **You can use input_fn to obtain training data:**

```
 def   input_fn ( filenames ,
 num_epochs = None ,
 shuffle = True ,
 skip_heade  r_lines = 0 ,
 batch_size = 200 ):
""" Generates   features   and   labels   for   training   or
 evaluation .
"""
 dataset  =  tf . data . TextLineDa  taset ( filenames ). skip (
 skip_heade  r_lines ). map ( parse_csv )
 if   shuffle :
 dataset  =  dataset . shuffle ( buffer_siz  e = batch_size  *  10
 )
 dataset  =  dataset . repeat ( num_epochs )
 dataset  =  dataset . batch ( batch_size )
 iterator  =  dataset . make_one_s  hot_iterat  or ()
 features  =  iterator . get_next ()
 return   features ,  parse_labe  l_column ( features . pop (
 LABEL_COLU  MN ))
 train_inpu  t  =  lambda :  input_fn (
 TRAIN_FILE  S ,
 batch_size = 40
)
#  Don ' t   shuffle   evaluation   data
 eval_input  =  lambda :  input_fn (
 EVAL_FILES ,
 batch_size = 40 ,
 shuffle = False
)
```

5. **Initiate Estimator.**

   **The following example uses the pre-defined TensorFlow's wide and deep model to build the Estimator:**

```
 tf . estimator . DNNLinearC  ombinedCla  ssifier (
 config = config ,
 linear_fea  ture_colum  ns = wide_colum  ns ,
 dnn_featur  e_columns = deep_colum  ns ,
 dnn_hidden  _units = hidden_uni  ts   or  [ 100 ,  70 ,  50 ,  25
 ]
)
```

6. **Train the models:**

```
 train_spec  =  tf . estimator . TrainSpec ( train_inpu  t ,
 max_steps = 1000
)
 exporter  =  tf . estimator . FinalExpor  ter (' census ',
 json_servi  ng_input_f  n )
 eval_spec  =  tf . estimator . EvalSpec ( eval_input ,
 steps = 100 ,
 exporters =[ exporter ],
 name =' census - eval '
```

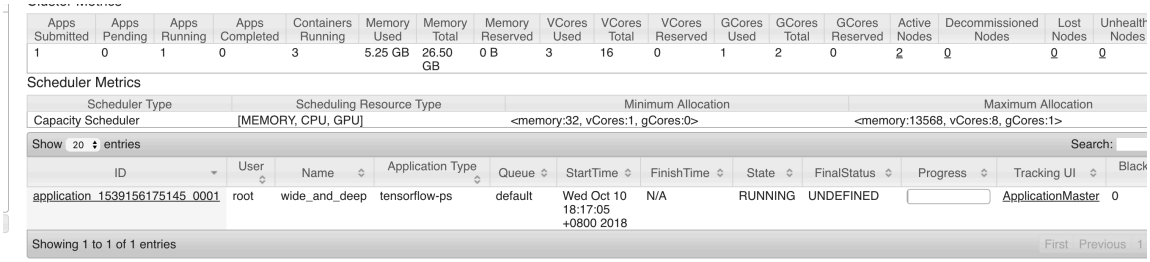
```
)
 tf . estimator . train_and_  evaluate ( estimator ,  train_spec
 ,  eval_spec )
```

**After the codes are complete, you can submit a task to your Data Science cluster. We recommend that you send the task to the cluster to perform standalone training using a standalone model. After verifying the task without code errors, you can submit a distributed task and specify worker and ps resources for training. An example command for submitting a task is as follows:**

```
el_submit  - t   tensorflow - ps  - a   wide_and_d  eep  - m
local  - x   True  - f  ./ - pn   1  - pc   1  - pm   2000  - wn
```

```
  1  -wc  1  -wg  1  -wm  2000  -c  python  census_sin
gle .
```

**The running status of the submitted task can be viewed in the YARN page.**



| Apps Submitted | Apps Pending | Apps Running | Apps Completed | Containers Running | Memory Used | Memory Total | Memory Reserved | VCores Used | VCores Total | VCores Reserved | GCores Used | GCores Total | GCores Reserved | Active Nodes | Decommissioned Nodes | Lost Nodes | Unhealth Nodes |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 1 | 0 | 3 | 5.25 GB | 26.50 GB | 0 B | 3 | 16 | 0 | 1 | 2 | 0 | 2 | 0 | 0 | 0 |

Scheduler Metrics

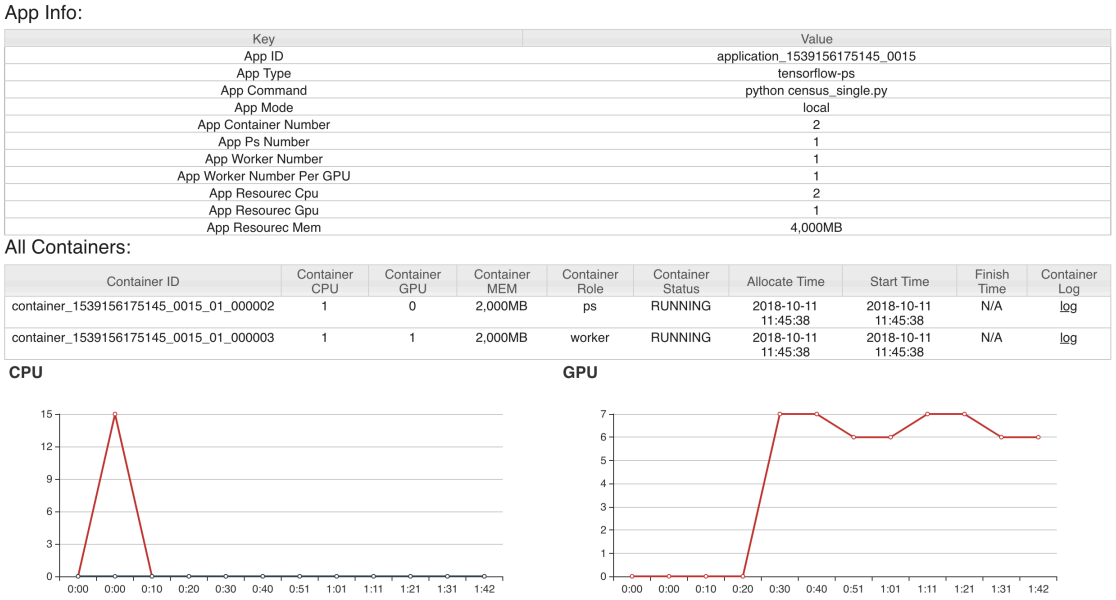
| Scheduler Type | Scheduling Resource Type | Minimum Allocation | Maximum Allocation |
|---|---|---|---|
| Capacity Scheduler | [MEMORY, CPU, GPU] | <memory:32, vCores:1, gCores:0> | <memory:13568, vCores:8, gCores:1> |

Show 20 entries Search:

| ID | User | Name | Application Type | Queue | StartTime | FinishTime | State | FinalStatus | Progress | Tracking UI | Black |
|---|---|---|---|---|---|---|---|---|---|---|---|
| application_1539156175145_0001 | root | wide_and_deep | tensorflow-ps | default | Wed Oct 10 18:17:05 +0800 2018 | N/A | RUNNING | UNDEFINED | | ApplicationMaster | 0 |

Showing 1 to 1 of 1 entries First Previous 1

**Click the ApplicationMaster link to view the running status and details of the task.**



App Info:

| Key | Value |
|---|---|
| App ID | application_1539156175145_0015 |
| App Type | tensorflow-ps |
| App Command | python census_single.py |
| App Mode | local |
| App Container Number | 2 |
| App Ps Number | 1 |
| App Worker Number | 1 |
| App Worker Number Per GPU | 1 |
| App Resourec Cpu | 2 |
| App Resourec Gpu | 1 |
| App Resourec Mem | 4,000MB |

All Containers:

| Container ID | Container CPU | Container GPU | Container MEM | Container Role | Container Status | Allocate Time | Start Time | Finish Time | Container Log |
|---|---|---|---|---|---|---|---|---|---|
| container_1539156175145_0015_01_000002 | 1 | 0 | 2,000MB | ps | RUNNING | 2018-10-11 11:45:38 | 2018-10-11 11:45:38 | N/A | log |
| container_1539156175145_0015_01_000003 | 1 | 1 | 2,000MB | worker | RUNNING | 2018-10-11 11:45:38 | 2018-10-11 11:45:38 | N/A | log |

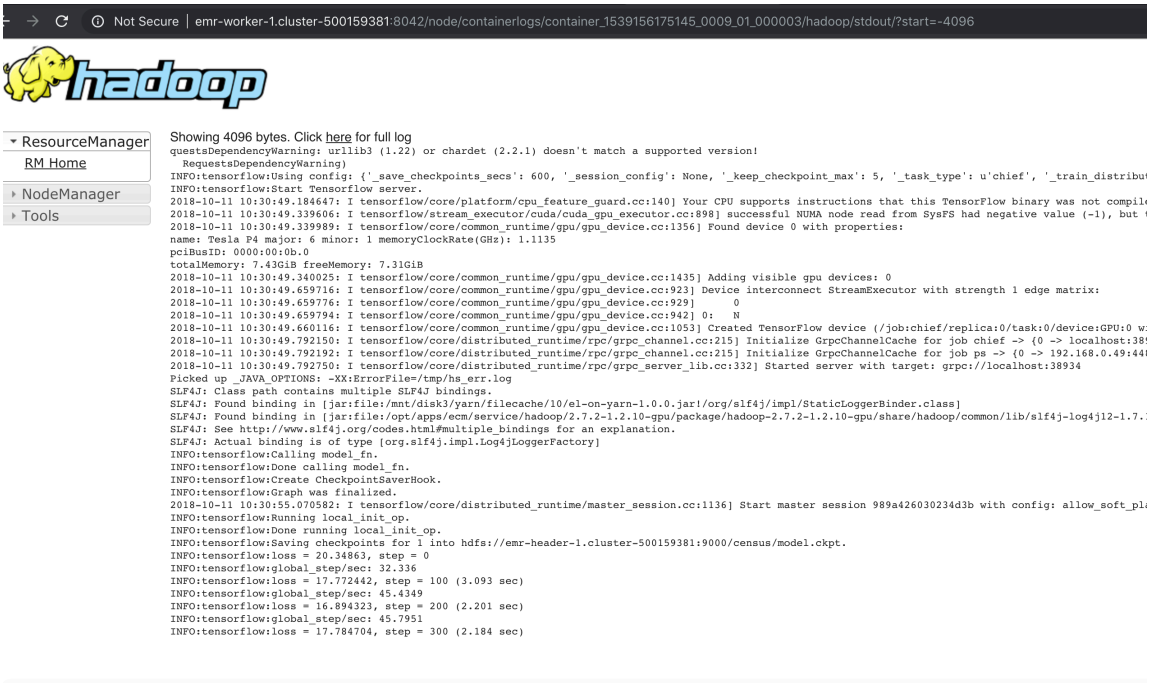
CPU




GPU




**Click log to go to ps or worker to view training information.**




In this example, after the training ends, you can find models in the HDFS path `/census` where models are generated.

```
[root@emr-header-1 ~]# hdfs dfs -ls /census
Found 9 items
-rw-r-----   2 hadoop hadoop        132 2018-10-11 10:34 /census/checkpoint
-rw-r-----   2 hadoop hadoop         40 2018-10-11 10:30 /census/events.out.tfevents.1539225054.emr-worker-1.cluster-500159381
-rw-r-----   2 hadoop hadoop    1839028 2018-10-11 10:30 /census/graph.pbtxt
-rw-r-----   2 hadoop hadoop   12406864 2018-10-11 10:31 /census/model.ckpt-1.data-00000-of-00001
-rw-r-----   2 hadoop hadoop       2463 2018-10-11 10:31 /census/model.ckpt-1.index
-rw-r-----   2 hadoop hadoop     870015 2018-10-11 10:31 /census/model.ckpt-1.meta
-rw-r-----   2 hadoop hadoop   12406864 2018-10-11 10:34 /census/model.ckpt-10000.data-00000-of-00001
-rw-r-----   2 hadoop hadoop       2463 2018-10-11 10:34 /census/model.ckpt-10000.index
-rw-r-----   2 hadoop hadoop     870015 2018-10-11 10:34 /census/model.ckpt-10000.meta
```

## Question descriptions

If the following errors display, check if there are empty lines in adult.data and adult.test.

```
 tensorflow . python . framework . errors_imp  l . InvalidArg
 umentError :  Expect   15   fields   but   have   0   in   record
 0
[[ Node :  DecodeCSV  =  DecodeCSV [ OUT_TYPE =[ DT_INT32 ,  DT_STRING
 ,  DT_INT32 ,  DT_STRING ,  DT_INT32 , ...,  DT_INT32 ,  DT_INT32 ,
 DT_INT32 ,  DT_STRI
 NG ,  DT_STRING ],  field_deli  m =",",  na_value ="",  use_quote_
 delim = true ]( ExpandDims ,  DecodeCSV / record_def  aults_0 ,
 DecodeCSV / record_def  aults_1 ,  D
 ecodeCSV / record_def  aults_2 ,  DecodeCSV / record_def  aults_3 ,
 DecodeCSV / record_def  aults_4 ,  DecodeCSV / record_def  aults_5 ,
 DecodeCSV / record_def  ault
 s_6 ,  DecodeCSV / record_def  aults_7 ,  DecodeCSV / record_def
 aults_8 ,  DecodeCSV / record_def  aults_9 ,  DecodeCSV / record_def
 aults_10 ,  DecodeCSV / record_
 defaults_1  1 ,  DecodeCSV / record_def  aults_12 ,  DecodeCSV /
 record_def  aults_13 ,  DecodeCSV / record_def  aults_14 )]]
```

```
[[ Node :  IteratorGe  tNext  =  IteratorGe  tNext [ output_sha  pes
 =[[?, 1 ], [?, 1 ], [?, 1 ], [?, 1 ], [?, 1 ], [?, 1 ], [?, 1 ], [?,
 1 ], [?, 1 ], [?, 1 ], [?, 1 ],
[?, 1 ], [?, 1 ], [?, 1 ]],  output_typ  es =[ DT_INT32 ,  DT_INT32
 ,  DT_INT32 ,  DT_STRING ,  DT_INT32 ,  DT_STRING ,  DT_INT32 ,
 DT_STRING ,  DT_STRING ,  DT_STRING
,  DT_STRING ,  DT_STRING ,  DT_STRING ,  DT_STRING ],  _device
 ="/ job : chief / replica : 0 / task : 0 / device : CPU : 0 "](
 OneShotIte  rator )]]
[[ Node :  global_ste  p / cond / pred_id_S6  15  =  _HostRecv [
 client_ter  minated = false ,  recv_devic  e ="/ job : ps / replica :
 0 / task : 0 / device : CPU : 0 ",  send_d
 evice ="/ job : chief / replica : 0 / task : 0 / device : GPU : 0 ",
 send_devic  e_incarnat  ion = 6104642431  418663740 ,  tensor_nam  e
 =" edge_602_g  lobal_step / cond / pred_
 id ",  tensor_typ  e = DT_BOOL ,  _device ="/ job : ps / replica : 0
 / task : 0 / device : CPU : 0 "]()]]
 2
```

# 10 Use Flink jobs to process OSS data

This topic describes how to create a Hadoop cluster by using E-MapReduce (EMR) and use Flink jobs to process Object Storage Service (OSS) data in the cluster.

## Prerequisites

- You have registered an Alibaba Cloud account. For more information, see Create an Alibaba Cloud account.
- You have activated EMR and OSS.
- You have authorized the Alibaba Cloud account. For more information, see #unique_19.

## Context

During practical applications, you always need to consume data stored in OSS. In EMR, you can run a Flink job to consume data stored in OSS buckets. You can perform the following steps to create a Flink job in EMR and run the Flink job on a Hadoop cluster to obtain and output the specified content of a file stored in OSS.

### Step 1: Prepare the environment

Before creating a Flink job, you must prepare the Maven and Java environment on your local host and create a Hadoop cluster in EMR. If you are using Maven 3.0 or later, we recommend that you use Java 2.0 or earlier to ensure compatibility.

1. Install Maven and Java on your local host.
2. Log on to the EMR console and create a Hadoop cluster. You must select Flink in the Optional Services field. For more information, see #unique_5.

### Step 2: Prepare testing data

Before creating a Flink job, you must upload testing data to OSS. The following is an example of uploading a file named `test.txt`. The file content is: Nothing is impossible for a willing heart. While there is a life, there is a hope.

1. Log on to the OSS console.

2. Create a bucket and upload the file to the bucket. For more information, see #unique_20 and #unique_21.

   The sample path of the uploaded file is `oss://emr-logs2/hengwu/test.txt`. Keep the path for later use.

    Note:
   After uploading the file, keep the OSS logon window open for later use.

### Step 3: Build a JAR file and upload it to OSS or the Hadoop cluster

Download EMR sample code aliyun-emapreduce-demo and compile the code to create a JAR file. You can upload the JAR file to the header node of the Hadoop cluster or an OSS bucket. The following is an example of uploading the JAR file to an OSS bucket.

1. Download EMR sample code aliyun-emapreduce-demo to your local disk.
2. Run the `mvn clean package -DskipTests` command to create the JAR file.

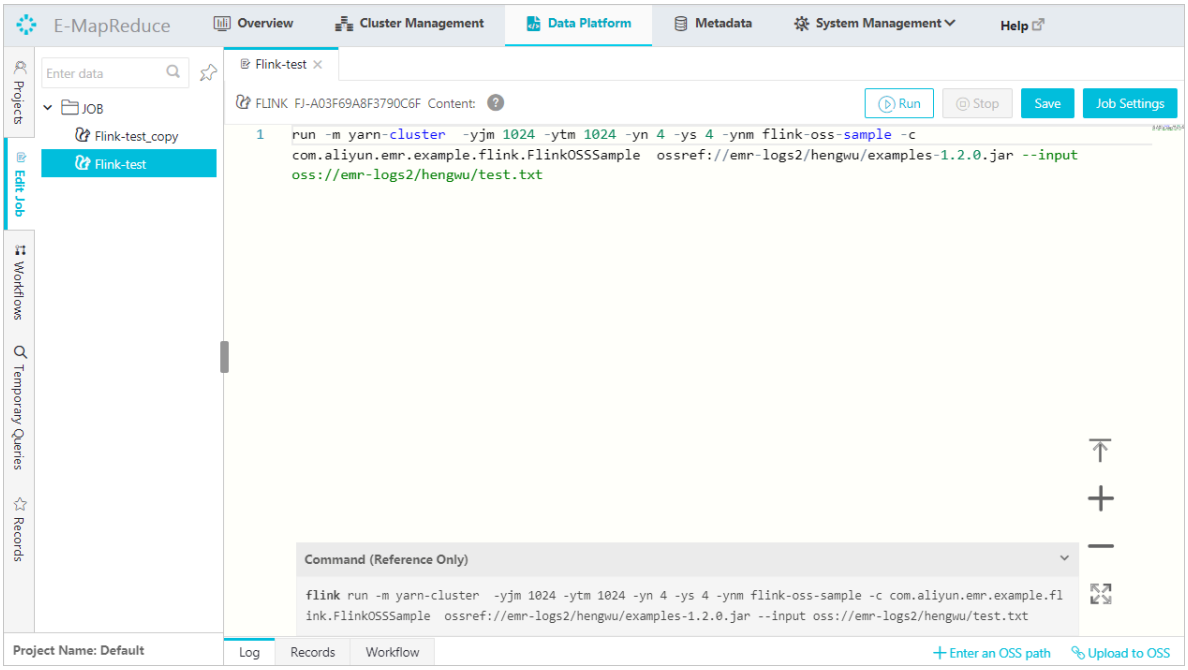
   The new JAR file is installed in the `../target/` directory, for example, `target/examples-1.2.0.jar`.
3. Go to the OSS console and upload the JAR file to an OSS directory.

   The sample path of the JAR file is `oss://emr-logs2/hengwu/examples-1.2.0.jar`. Keep the path for later use.

### Step 4: Create and run a Flink job

1. Log on to the EMR console.
2. On the Data Platform tab, create a project. For more information, see #unique_22.
3. Open the new project, select the Edit Job tab, and create a job with the type of Flink.

4. After the new Flink job is created, specify the content of the job.




The job content is a snippet of code. An example is shown as follows.

```
run -m yarn-cluster -yjm 1024 -ytm 1024 -yn 4
 -ys 4 -ynm flink-oss-sample -c com.aliyun.emr
.example.flink.FlinkOSSSample ossref://emr-logs2/
hengwu/examples-1.2.0.jar --input oss://emr-logs2
/hengwu/test.txt
```

Key parameters in the preceding code are described as follows:

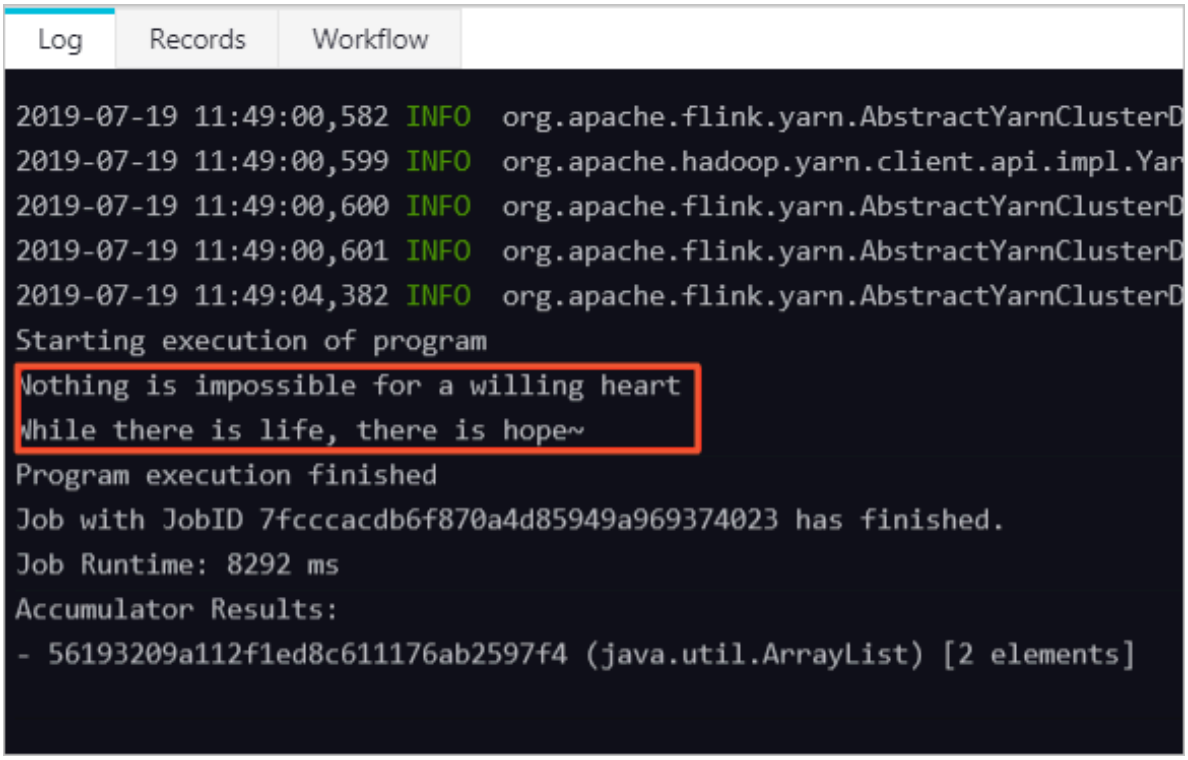
- *ossref://emr-logs2/hengwu/examples-1.2.0.jar*: indicates the path of the uploaded JAR file.
- *oss://emr-logs2/hengwu/test.txt*: indicates the path of the testing data.

> **Note:**
> Replace the value of each parameter with values based on the configurations in the Step 1: Prepare the environment and Step 3: Build a JAR file and upload it to OSS or the Hadoop cluster topics.

5. After the job configuration is complete, click Run in the upper-right corner, and select the name of the new Hadoop cluster in the Target Cluster field.

6. Click OK to run the Flink job.

   When the job is running, the Log window appears. After the job is complete, the file content is obtained from an OSS bucket and output to logs. At this point, the Flink job that runs on an EMR cluster to consume OSS data is complete.




Step 5: View the logs and details of the job (Optional)

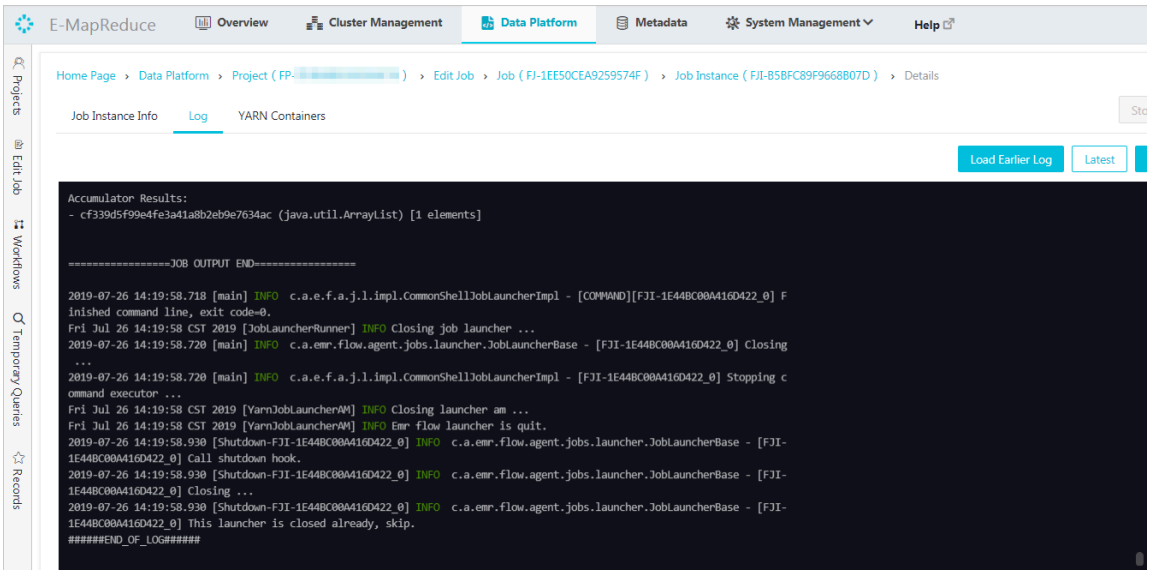
You can view the logs and details of the job to identify the cause of a job failure and details of the job.

1. View the logs of the job.

   You can view logs in the EMR console or on an SSH client.

   - Log on to the EMR console to view logs.

     After submitting a job in the console, you can open the Details page of a job listed on the Records tab. On the Details page, you can view the results of the job.

   - You can log on to the header node of a Hadoop cluster by using SSH to view logs.

     By default, the logs of a Flink job are stored in the `/mnt/disk1/log/flink/flink-<user>-client-<hostname>.log` file based on the configurations in the log4j file. For more information about detailed configurations, see the `/etc/ecm/flink-conf/log4j-yarn-session.properties` file.

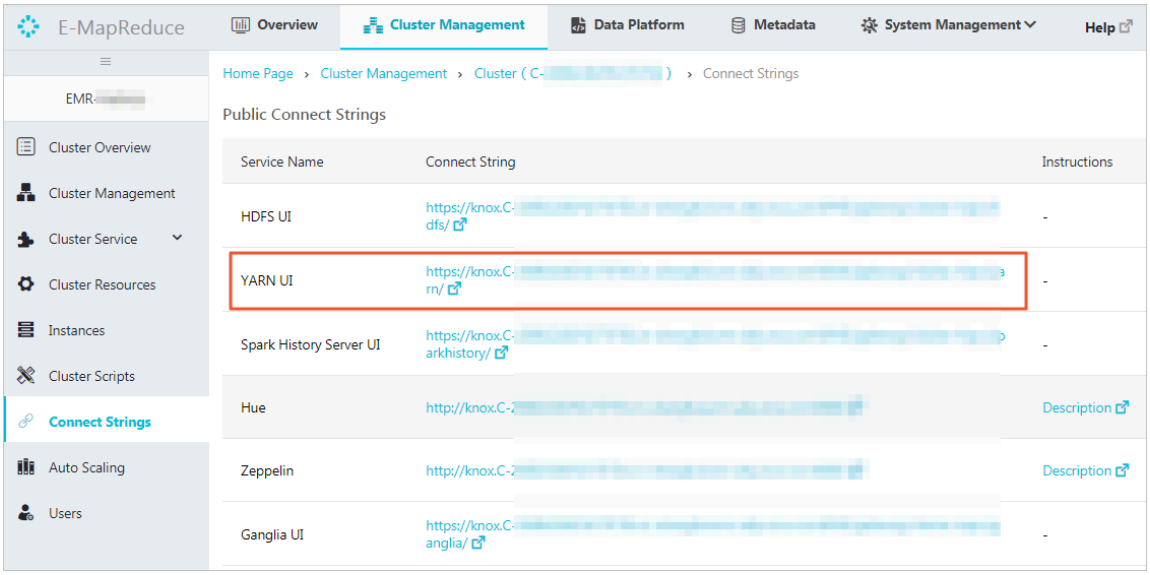
     The `user` field indicates the account with which you submit the Flink job. The `hostname` field indicates the name of the instance to which you submit the job. Assume that you log on as a root user and submit a Flink job on the emr-header-1 instance. In this case, the log path is `/mnt/disk1/log/flink/flink-flink-historyserver-0-emr-header-1.cluster-126601.log`.

2. View the details of the job.

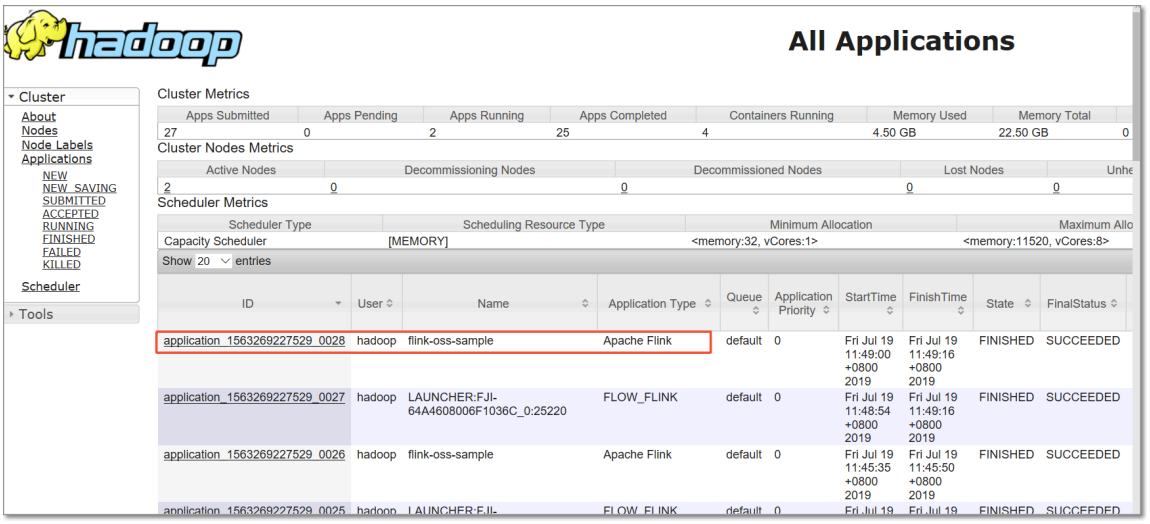
   You can use Yarn UI. You can access Yarn UI by using SSH and Knox. For more information about SSH, see #unique_23. For more information about Knox, see

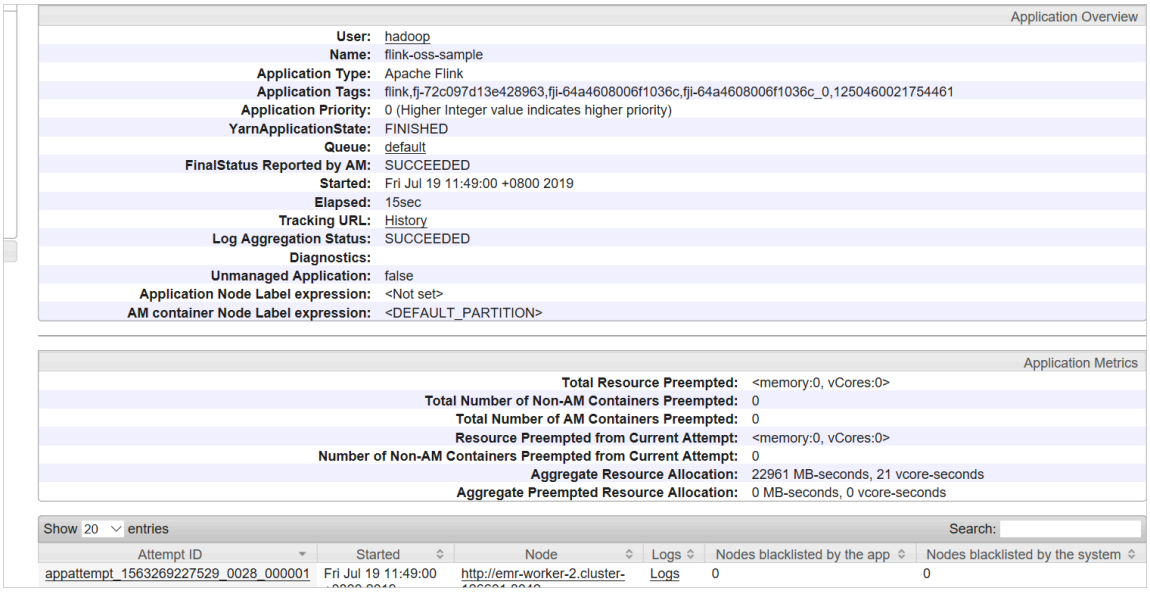
#unique_24 and Access links and ports. The following takes Knox as an example to describe how to view the details of a job.

a) On the Connect Strings tab of the Hadoop cluster, click the link next to Yarn UI to open the Hadoop console.




b) In the Hadoop console, click the ID of the job to view the details of the job.






c) If you need to view a list of running Flink jobs, you can click the link next to Tracking URL on the Details page. The Flink Dashboard page that appears displays the list of running Flink jobs.

   You can also access http://emr-header-1:8082 to view a list of completed jobs.

# 11 Connect to ApsaraDB for HBase using E-MapReduce Hive

This topic describes how to connect E-MapReduce Hive and ApsaraDB for HBase. The analysis of HBase tables is based on the connection between Hive and ApsaraDB for HBase.

 Note:
ApsaraDB for HBase will be integrated into Spark. We recommend that you use Spark to analyze HBase data at that time.

## Preparations

- Purchase a Pay-As-You-Go EMR cluster and create configurations based on the actual scenarios. Note: Make sure ApsaraDB for HBase and the EMR cluster are in the same VPC. We recommend that you do not enable High Availability for the cluster.
- Add the IP addresses of all nodes in the EMR cluster to the whitelist of ApsaraDB for HBase.
- You can view the endpoint of ZooKeeper that is built in Hive in the ApsaraDB for HBase console.
- You need to contact the Alibaba Cloud team to open the HDFS ports of an ApsaraDB for HBase for you.

## Procedures

1. Modify Hive configurations
   - Go to the Hive configuration directory `/ etc / ecm / hive - conf /`.
   - Modify the `hbase - site . xml` file by setting the value of the `hbase . zookeeper . quorum` property to the endpoint of ZooKeeper that is built in HBase.

```
< property >
           < name > hbase . zookeeper . quorum </ name >
           < value > hb - bp1mhyea77  54bpigt - 001 . hbase . rds
 . aliyuncs . com , hb - bp1mhyea77  54bpigt - 002 . hbase . rds
 . aliyuncs . com , hb - bp1mhyea77  54bpigt - 003 . hbase . rds .
aliyuncs . com </ value >
```

```
        </ property >
```

2. **Connect to an HBase table using a Hive table**

   **Create a table in Hive using the HBase handler. By doing this, the same table is created in ApsaraDB for HBase as well.**

   a. **Start the Hive command-line interface (CLI).**

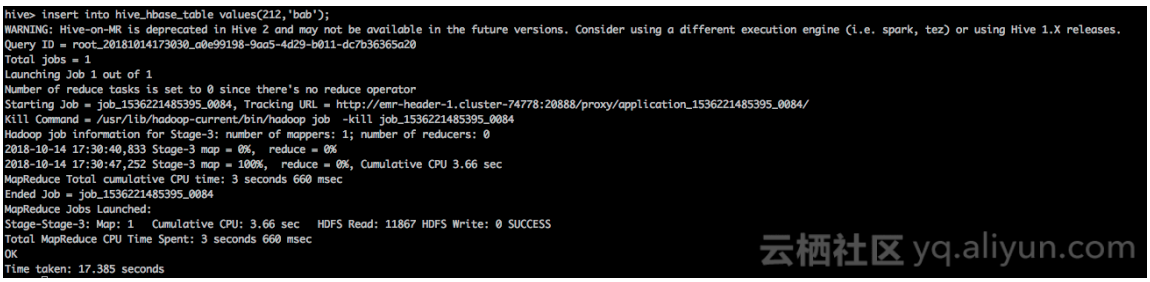

   b. **Use the following statement to create a table in Hive.**

```
CREATE   TABLE   hive_hbase  _table ( key   int ,  value   string
)
```

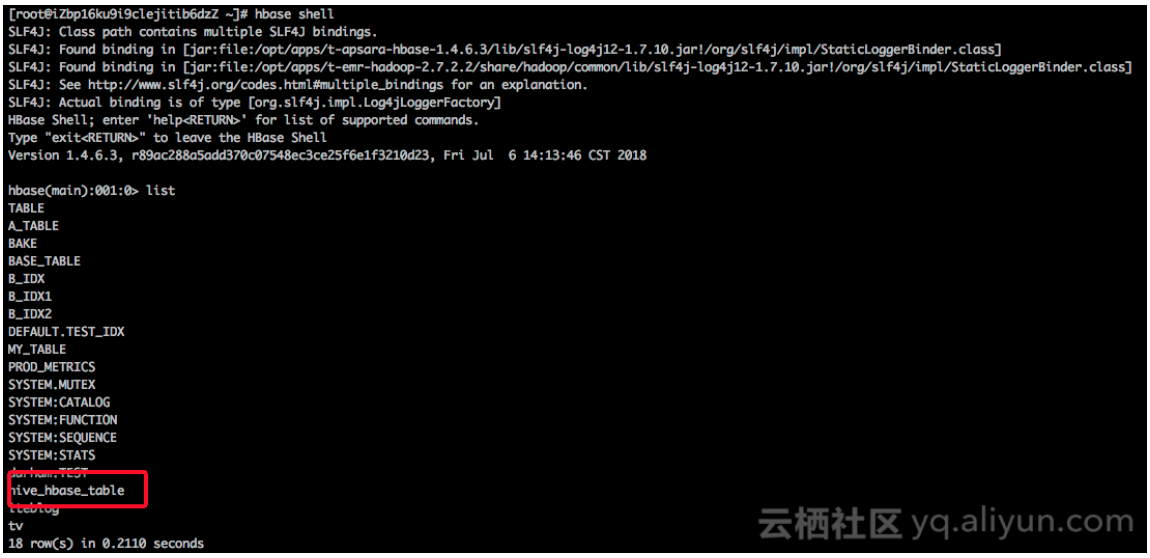
```
STORED   BY  ' org . apache . hadoop . hive . hbase . HBaseStora
geHandler '
WITH   SERDEPROPE  RTIES  (" hbase . columns . mapping " = ": key
, cf1 : val ")
```

```
TBLPROPERT  IES  (" hbase . table . name " = " hive_hbase  _table
", " hbase . mapred . output . outputtabl  e " = " hive_hbase
_table ");
```

c. Insert data to the HBase table in Hive.

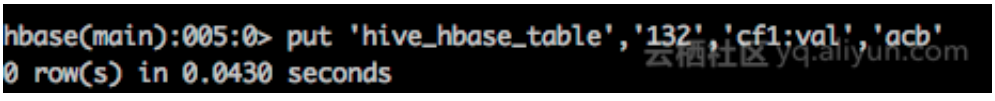



d. Verify that the HBase table has been created and the data has been inserted to the table.

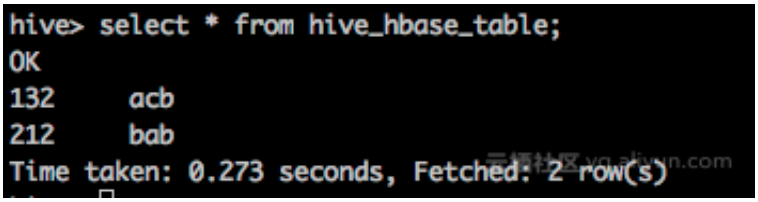




e. Write data to the HBase table using the put command.




Select all data from the table in Hive.




f. Delete the table in Hive using the drop command. The table in HBase is deleted as well, which is to be verified in the subsequent step.

```
hive>
    >
    >
    > drop table hive_hbase_table;
OK
Time taken: 6.307 seconds
```


View the contents on the table in HBase using the scan command. An error message appears showing the table does not exist.

```
hbase(main):008:0* scan 'hive_hbase_table'
ROW                                                    COLUMN+CELL

ERROR: Unknown table hive_hbase_table!
```


Note:

Existing HBase tables can be connected using the Hive external tables. Deleting a Hive external table does not cause the deletion of the corresponding HBase table.

g. Create a table in ApsaraDB for HBase and write test data to the table using the put command.

```
hbase(main):020:0* create 'hbase_table','f'
0 row(s) in 1.3010 seconds

=> Hbase::Table - hbase_table
hbase(main):021:0> put 'hbase_table','1122','f:col1','hello'
0 row(s) in 0.0190 seconds

hbase(main):022:0> put 'hbase_table','1122','f:col2','hbase'
0 row(s) in 0.0110 seconds
```



h. Create a Hive external table to connect to an HBase table and select all data from the HBase table.

```
hive> create external table hbase_table(key int, col1 string, col2 string)
    > STORED BY 'org.apache.hadoop.hive.hbase.HBaseStorageHandler'
    > WITH SERDEPROPERTIES ("hbase.columns.mapping" = "f:col1,f:col2")
    > TBLPROPERTIES("hbase.table.name" = "hbase_table", "hbase.mapred.output.outputtable" = "hbase_table");
OK
Time taken: 0.129 seconds
hive> select * from hbase_table;
OK
1122    hello   hbase
Time taken: 0.181 seconds, Fetched: 1 row(s)
hive>
```



i. Verify that deleting the Hive external table does not cause the deletion of the corresponding HBase table.

```
hive> drop table hbase_table;
OK
Time taken: 0.102 seconds
hive>
```



```
hbase(main):023:0> scan 'hbase_table'
ROW                                             COLUMN+CELL
 1122                                           column=f:col1, timestamp=1539510170256, value=hello
 1122                                           column=f:col2, timestamp=1539510181752, value=hbase
1 row(s) in 0.0160 seconds
```



## Summary

For more operations on HBase using Hive, see HBase Integration. The operations in this topic are based on Hive installed on an Alibaba Cloud EMR cluster. Operations based on Hive installed on a custom MapReduce cluster of ECS instances are similar. Note: Configuration items in the configuration file `hbase-site.xml` of Hive may be different from those of ApsaraDB for HBase. You only need to configure the

`hbase.zookeeper.quorum` property for connecting to ApsaraDB for HBase using Hive.

# 12 Use EMR for real-time MySQL binlog transmission

This section describes how to use the SLS plug-in function of Alibaba Cloud and the E-MapReduce cluster to implement quasi-real-time transmission of MySQL binlog.

## Basic architecture

RDS -> SLS -> Spark Streaming -> Spark HDFS

The preceding links contain three processes:

1. How to collect RDS binlog to SLS.
2. How to read and analyze the logs in SLS through Spark Streaming.
3. How to save the logs read and processed in the second link to Spark HDFS.

## Prepare the environment

1. Install a MySQL database (using MySQL protocol, such as RDS and DRDS), and enable the log-bin function. Configure the binlog type to ROW mode. (RDS is enabled by default.)
2. Enable the SLS service.

## Procedure

1. Check the MySQL database environment.
   a. View whether the log-bin function is enabled.

```
 mysql >  show   variables   like  " log_bin ";
+---------------+-------+
|  Variable_n  ame  |  Value  |
+---------------+-------+
|  log_bin        |  ON     |
+---------------+-------+
 1   row   in   set  ( 0 . 02   sec )
```

   b. View the binlog type.

```
 mysql >  show   variables   like  " binlog_for  mat ";
+---------------+-------+
|  Variable_n  ame  |  Value  |
+---------------+-------+
|  binlog_for  mat  |  ROW    |
+---------------+-------+
```

```
1 row in set ( 0 . 03 sec )
```

2. Add user permissions. You can also add user permissions directly from the RDS console.

```
CREATE USER canal IDENTIFIED BY ' canal ';
GRANT SELECT , REPLICATIO N SLAVE , REPLICATIO N CLIENT
ON *. * TO ' canal '@'%';
FLUSH PRIVILEGES ;
```

3. Add the corresponding configuration file for the SLS service, and check if the data is collected properly.

   a. Add the corresponding project and logstore in the SLS console. For example, create a project named canaltest and a logstore named canal.

   b. Configure SLS: create a file named user_local_config.json under the directory of /etc/ilogtail.

```
{
" metrics ": {
   "## 1 . 0 ## canaltest $ plugin - local ": {
       " aliuid ": "****",
       " enable ": true ,
       " category ": " canal ",
       " defaultEnd point ": "*******",
       " project_na me ": " canaltest ",
       " region ": " cn - hangzhou ",
       " version ": 2
       " log_type ": " plugin ",
       " plugin ": {
           " inputs ": [
               {
                   " type ": " service_ca nal ",
                   " detail ": {
                       " Host ": "*****",
                       " Password ": "****",
                       " ServerID ": ****,
                       " User " : "***",
                       " DataBases ": [
                           " yourdb "
                       ],
                       " IgnoreTabl es ": [
                           "\\ S + _inner "
                       ],
                        " TextToStri ng " : true
                   }
               }
           ],
           " flushers ": [
               {
                   " type ": " flusher_sl s ",
                   " detail ": {}
               }
           ]
       }
   }
}
```

```
}
```

The information such as host and password in detail is MySQL database information, and the user information is the user name authorized previously . AliUid, defaultEndpoint, project_name, and category are information related with users and SLS. Fill in the information according to your actual situation.

c. Wait about 2 minutes to see if the log data has been uploaded successfully in the SLS console.

If the log data acquisition is not successful, view the acquisition log of SLS based on its prompt for troubleshooting.

4. Prepare and compile the code to jar package, and upload it to OSS.

a. Copy the example code of EMR using Git and modify the code. The command is as follows: `git clone https :// github . com / aliyun / aliyun - emapreduce - demo . git` . The example code includes the LoghubSample class, which is primarily used to capture and print data from SLS. The modified code is as below:

```
package com . aliyun . emr . example
import org . apache . spark . SparkConf
import org . apache . spark . storage . StorageLev el
import org . apache . spark . streaming . aliyun . logservice .
LoghubUtil s
import org . apache . spark . streaming .{ Millisecon ds ,
StreamingC ontext }
object LoghubSamp le {
def main ( args : Array [ String ]): Unit = {
if ( args . length < 7 ) {
 System . err . println (
  """ Usage : bin / spark - submit -- class LoghubSamp le
examples - 1 . 0 - SNAPSHOT - shaded . jar
     |
     |
  """. stripMargi n )
 System . exit ( 1 )
}
 val loghubProj ect = args ( 0 )
 val logStore = args ( 1 )
 val loghubGrou pName = args ( 2 )
 val endpoint = args ( 3 )
 val accessKeyI d = args ( 4 )
 val accessKeyS ecret = args ( 5 )
 val batchInter val = Millisecon ds ( args ( 6 ). toInt *
 1000 )
 val conf = new SparkConf (). setAppName (" Mysql Sync ")
//     conf . setMaster (" local [ 4 ]");
 val ssc = new StreamingC ontext ( conf , batchInter val
 )
 val loghubStre am = LoghubUtil s . createStre am (
  ssc ,
  loghubProj ect ,
  logStore ,
```

```
  loghubGrou  pName ,
  qendpoint ,
  1 ,
  accessKeyI  d ,
  accessKeyS  ecret ,
  StorageLev  el . MEMORY_AND  _DISK )
 loghubStre  am . foreachRDD ( rdd  =>
    rdd . saveAsText  File ("/ mysqlbinlo  g ")
)
 ssc . start ()
 ssc . awaitTermi  nation ()
}
}
```

The main change is as follows: `loghubStre  am . foreachRDD ( rdd  => rdd . saveAsObje  ctFile ("/ mysqlbinlo  g ") )`. When the example code is run in the EMR cluster, the data that flows out of Spark Streaming will be saved in HDFS of EMR.

Note:

- To run the example code locally, create a Hadoop cluster in the local environment in advance.
- Because the Spark SDK of EMR is updated, its example code is old and cannot directly transfer the AccessKey ID and AccessKey Secret of OSS in the parameter. You need to set the Spark SDK with the SparkConf constructor, as shown in the following figure:

```
trait   RunLocally  {
val   conf  =  new   SparkConf (). setAppName ( getAppName ).
setMaster (" local [ 4 ]")
conf . set (" spark . hadoop . fs . oss . impl ", " com .
aliyun . fs . oss . nat . NativeOssF  ileSystem ")
conf . set (" spark . hadoop . mapreduce . job . run - local
", " true ")
conf . set (" spark . hadoop . fs . oss . endpoint ", "
YourEndpoi  nt ")
conf . set (" spark . hadoop . fs . oss . accessKeyI  d ", "
YourId ")
conf . set (" spark . hadoop . fs . oss . accessKeyS  ecret ",
" YourSecret ")
conf . set (" spark . hadoop . job . runlocal ", " true ")
conf . set (" spark . hadoop . fs . oss . impl ", " com .
aliyun . fs . oss . nat . NativeOssF  ileSystem ")
conf . set (" spark . hadoop . fs . oss . buffer . dirs ", "/
mnt / disk1 ")
val   sc  =  new   SparkConte  xt ( conf )
def   getAppName :  String
```

```
    }
```

- During local debugging, you need to change /mysqlbinlogloghubStream.foreachRDD(rdd => in rdd.saveAsObjectFile("/mysqlbinlog") ) to the local HDFS address.

b. Compile code.

After local debugging is complete, you can run the following command to package and compile the code:

```
mvn clean install
```

c. Upload the jar package.

Create a directory on an OSS instance where the bucket is qiaozhou-EMR/jar, and upload examples-1.1-shaded.jar under the directory of /target/shaded to the OSS directory through the OSS console or the SDK of OSS. The uploaded jar package address is oss://qiaozhou-EMR/jar/examples-1.1-shaded.jar. This address will be used later.

5. Create an EMR cluster and tasks, and run the execution plans.

a. Create an EMR cluster in the EMR console, which takes about 10 minutes.

b. Create a job of the Spark type.

Replace `SLS_endpoi nt` `$ SLS_access _id` `$ SLS_secret _key` with your actual values. Make sure that the order of the parameters is correct. Otherwise, errors may be reported.

```
-- master yarn -- deploy - mode client -- driver - memory
 4g -- executor - memory 2g -- executor - cores 2 -- class
  com . aliyun . EMR . example . LoghubSamp le ossref ://
 EMR - test / jar / examples - 1 . 1 - shaded . jar canaltest
```

```
canal  sparkstrea  ming  $ SLS_endpoi  nt  $ SLS_access  _id  $
SLS_secret  _key  1
```

c. After the execution plan is created, bind jobs to the EMR cluster. Start to run the jobs.

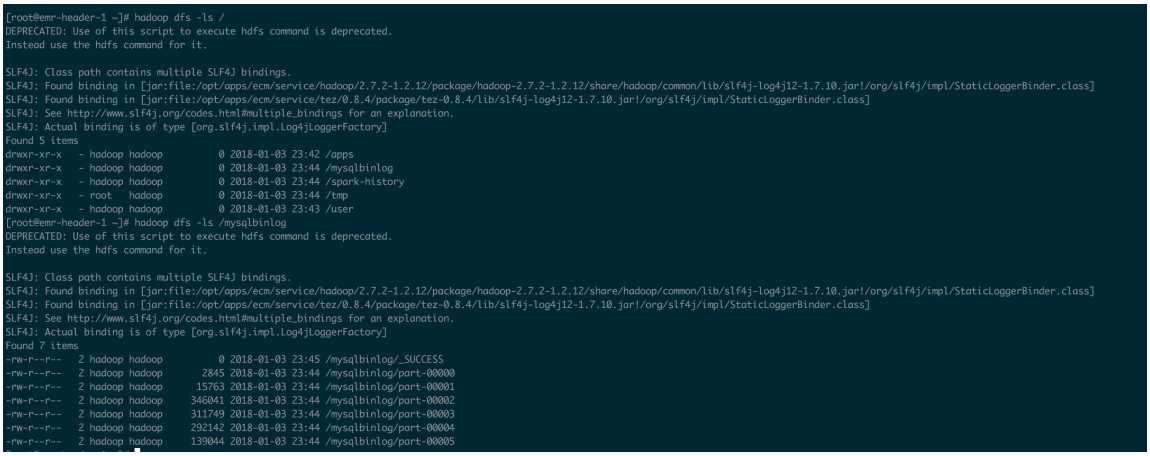
d. Search for the IP address of the master node.

After you login through SSH, run the following command:

```
hadoop  fs  - ls  /
```

You can see the directory at the beginning of mysqlbinlog, and view the mysqlbinlog file with the following command:

```
hadoop  fs  - ls  / mysqlbinlo  g
```




You can also run `hadoop  fs  - cat  / mysqlbinlo  g / part - 00000` command to view the file content.

6. Troubleshoot.

If you don’t see the normal results, you can troubleshoot problems in the running records of EMR.

# 13 Run Flume on a Gateway node to synchronize data

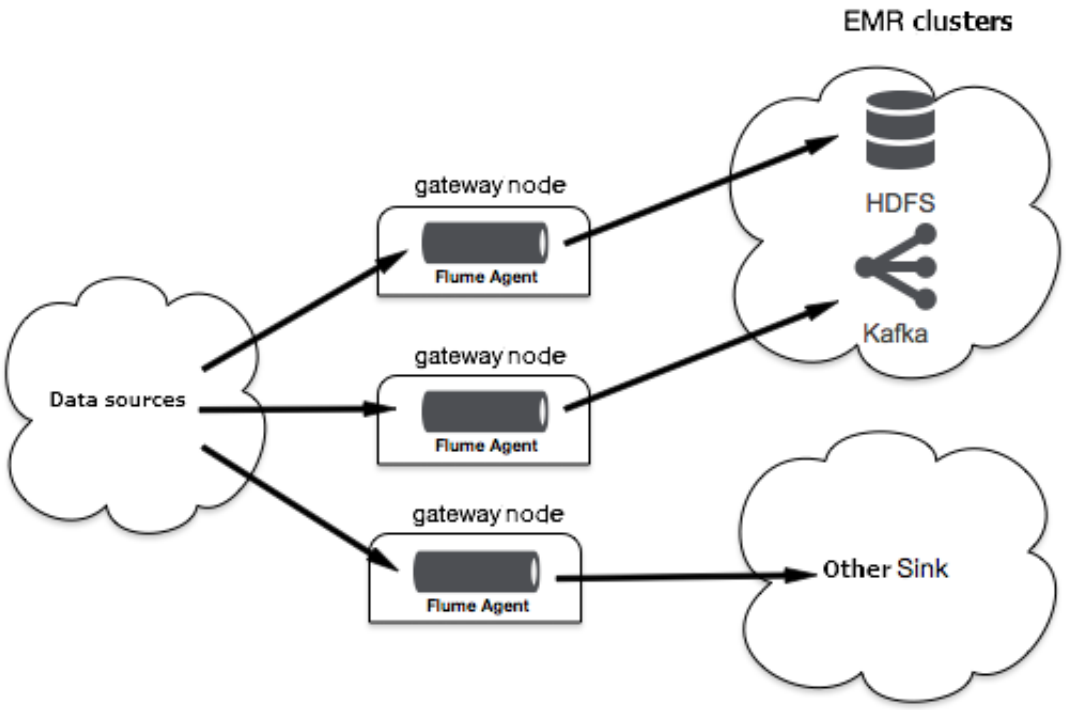
This topic describes how to run Flume on a Gateway node to synchronize data based on Alibaba Cloud E-MapReduce (EMR) V3.17.0 and later versions.

## Background

EMR has supported Apache Flume since V3.16.0 and has supported default monitoring since V3.17.0.

- Basic data flows

  Running Flume on Gateway nodes avoids the impact on EMR Hadoop clusters. Basic data flows that are streamed through Flume agents installed on Gateway nodes are shown in the following figure.



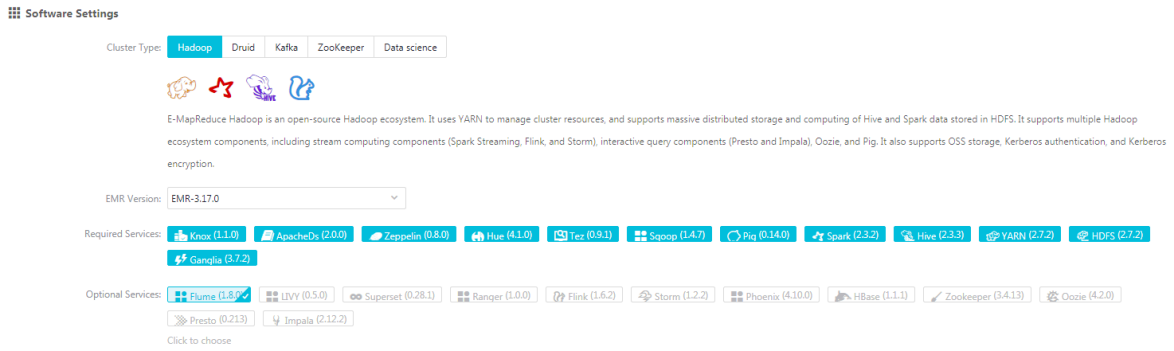

## Prepare the environment

The test is performed using EMR that is deployed in the China East 1 (Hangzhou) region. The version of EMR is V3.17.0. The components required for this test are as follows.

- Flume: 1.8.0

You can use EMR to automatically create a Hadoop cluster. For more information, see Create a cluster.

- Click Create Cluster, click Flume for the cluster type, and select Flume from Optional Services.




- Create a Gateway node and associate it to the Hadoop cluster created in the previous step.

## Procedure

- Run Flume
  - The default path of Flume configuration files is `/etc/ecm/flume-conf`. See Use Flume for modifying the configuration file `flume.properties` for Flume agents. After the modification, use the following command to run a Flume agent.

```
nohup flume-ng agent -n a1 -f flume.properties &
```

  - You can use the `-c` flag or the `--conf` flag to replace the default configuration file with a custom file. For example:

```
nohup flume-ng agent -n a1 -f flume.properties -
c path-to-flume-conf &
```

**Notice:**

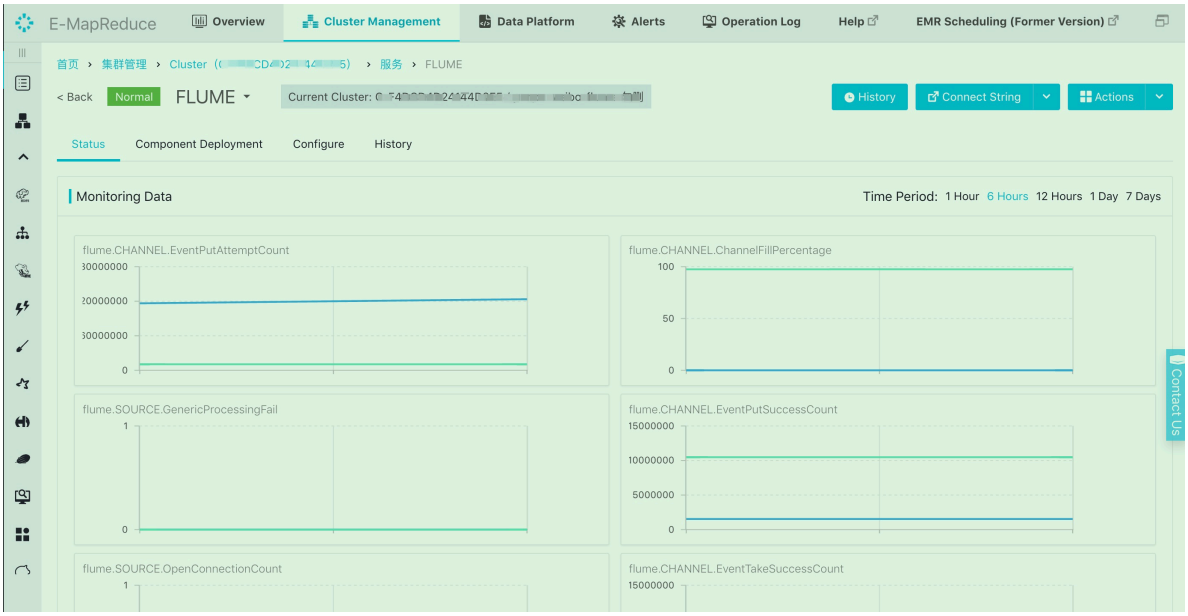
For more information, see Use Flume. You need to add the `zookeeperQuorum` configuration item to the *flume.properties* configuration file when the Flume agents installed on Gateways use sinks to write data to HBase. For example:

```
a1.sinks.k1.zookeeperQuorum = emr-header-1.cluster-46349:2181
```

The hostname of the ZooKeeper cluster `emr-header-1.cluster-46349` is the value of the `hbase.zookeeper.quorum` configuration item in the */etc/ecm/hbase-conf/hbase-site.xml* file.

- View monitoring information

  Monitoring data of Flume agents is displayed in the cluster console by default. On the Clusters and Services page, click FLUME to jump to the cluster console as shown in the following figure.




**Notice:**

Monitoring data is classified by the components (sources, channels, or sinks) of Flume agents. For example, CHANNEL.channel1 represents monitoring data of the channel1 channel component. Note: Avoid using the same component name when configuring different agents.

Refer to the official Flume website for viewing monitoring data of Flume agents using Ganglia by creating proper configurations. After doing this, monitoring data of Flume agents will not be displayed in the console.

- View logs

  By default, the log path of a Flume agent is `/ mnt / disk1 / log / flume /${ flume - agent - name }/ flume . log` . You can modify the `/ etc / ecm / flume - conf / log4j . properties` configuration file to change the log path. However, we recommend that you do not change the default log path.

   **Notice:**
  A log path contains a Flume agent name. Provide a unique name for each agent to avoid logs of different agents to be stored in the same directory.

# 14 Isolate OSS data of different users

This topic describes how to use Resource Access Management (RAM) to isolate Object Storage Service (OSS) data of different users.

## Prerequisite

An Alibaba Cloud account is created.

## Background

E-MapReduce allows you to use RAM to isolate data of different users.

## Step 1: Log on to the RAM console

1. Log on to the RAM console by using an Alibaba Cloud account.

## Step 2: Create a RAM user

1. In the left-side navigation pane, click Identities, and click Users.
2. Click Create User.

    Note:
   To create multiple RAM users at a time, click Add User.
3. Specify the Logon Name and Display Name parameters.
4. Under Access Mode, select Console Password Logon or Programmatic Access.

    Note:
   We recommend that you select only one access mode for the RAM users to ensure the security of your Alibaba Cloud account. This prevents RAM users who have terminated their employment contracts with the company from accessing Alibaba Cloud resources.
5. Click OK.

## Step 3: Create permission policies

In addition to providing the default permission policies, RAM allows you to customize permission policies for flexible authorization. You can create multiple permission policies based on your needs.

1. In the left-side navigation pane, click Permissions, and click Policies.
2. On the page that appears, click Create Policy.

3. On the Create Custom Policy page, specify the Policy Name and Note parameters.
4. Select Script in Configuration Mode.

   For more information about how to configure a permission policy in script mode, see the permission policy syntax and structure. In the following example, two permission policies are created in script mode:

| Test environment (test-bucket) | Production environment (prod-bucket) |
| --- | --- |
| { " Version ": " 1 ", " Statement ": [ { " Effect ": " Allow ", " Action ": [ " oss : ListBucket s " ], " Resource ": [ " acs : oss :*:*:*" ] }, { " Effect ": " Allow ", " Action ": [ " oss : Listobject s ", " oss : GetObject ", " oss : PutObject ", " oss : DeleteObje ct " ], " Resource ": [ " acs : oss :*:*: test - bucket ", " acs : oss :*:*: test - bucket /*" ] } ] } | { " Version ": " 1 ", " Statement ": [ { " Effect ": " Allow ", " Action ": [ " oss : ListBucket s " ], " Resource ": [ " acs : oss :*:*:*" ] }, { " Effect ": " Allow ", " Action ": [ " oss : Listobject s ", " oss : GetObject ", " oss : PutObject " ], " Resource ": [ " acs : oss :*:*: prod - bucket ", " acs : oss :*:*: prod - bucket /*" ] } ] } |

   After the preceding permission policies are granted to a RAM user, the RAM user is subject to the following restrictions in the E-MapReduce console:

   - All buckets are displayed on the OSS selection page for creating clusters, jobs, and execution plans, but only the authorized buckets can be accessed.
   - Only the contents of the authorized buckets are accessible.
   - Only the authorized buckets can be read and written. An error is returned if the RAM user performs read or write operation on unauthorized buckets.
5. Click OK.

### Step 4: Grant permissions to the RAM user

1. In the left-side navigation pane, click Identities, and click Users.
2. In the User Logon Name/Display Name column, find the target RAM user.
3. Click Add Permissions. On the page that appears, the principle is automatically filled in.
4. In the Policy Name column, select the target policies by clicking the corresponding rows.

    Note:
   You can click X in the section on the right side of the page to delete the selected policy.
5. Click OK.
6. Click Finished.

### (Optional) Step 5: Authorize the RAM user to log on to the Alibaba Cloud console

If the console logon permission is not granted to the RAM user when the RAM user is created, you can grant the permission to the RAM user as follows:

1. In the left-side navigation pane, click Identities, and click Users.
2. In the User Logon Name/Display Name column, click the username of the target RAM user.
3. In the Console Logon Management section of the Authentication tab, click Modify Logon Settings.
4. Under Console Password Logon, select Enabled.
5. Click OK.

### Step 6: Log on to the E-MapReduce console as the RAM user

1. Log on to the Alibaba Cloud console as the RAM user.
2. After logging on to the console, select E-MapReduce.

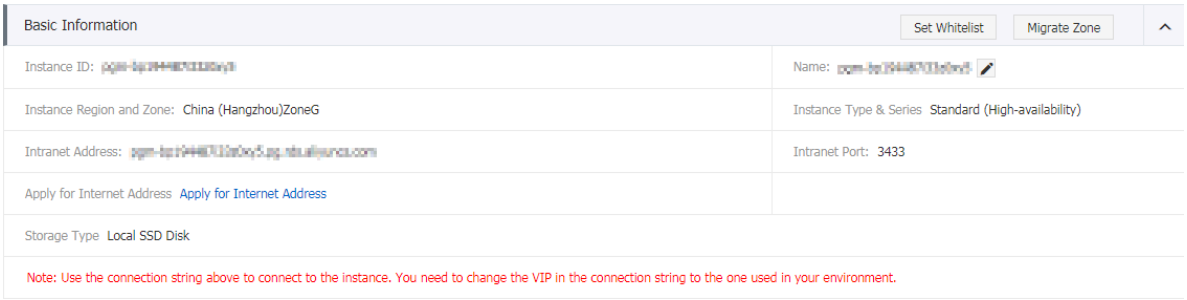
# 15 Configure a network connection for using Sqoop to transfer data from a database to an EMR cluster

When you need to transfer data from external databases to your EMR cluster, make sure that the networks are connected. This topic describes how to configure network connections for accessing ApsaraDB for RDS instances, user-created databases hosted on ECS, and on-premises databases.

## ApsaraDB for RDS

- Classic network

  We recommend that you use an EMR cluster deployed in the classic network to access a classic network RDS instance. You can set internal and public IP addresses for classic network RDS instances. Sqoop synchronizes data by running map tasks on the master node and worker nodes. However, only the master node of a classic network EMR cluster can access the public network. You need to access the internal IP address of the RDS instance for Sqoop. Make sure that the internal IP address of the EMR cluster is in the whitelist of the RDS instance.

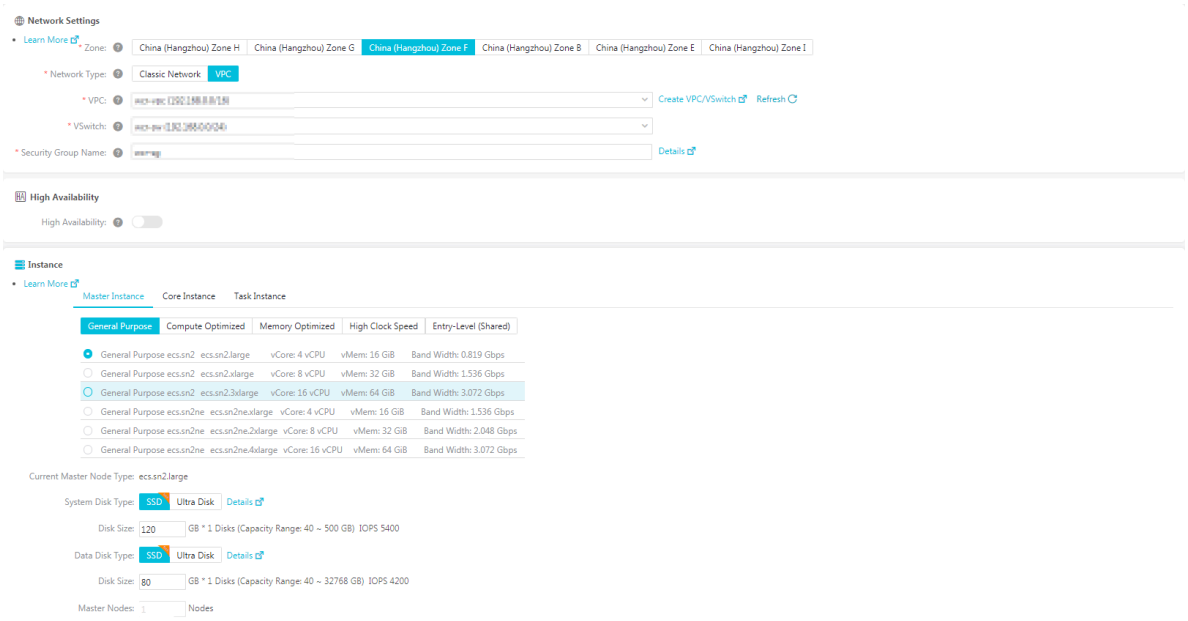
  
  

  For more information about how to create a classic network EMR cluster, see Create a cluster.

- VPC

  If the RDS is in a VPC network, you must specify a VPC network for the EMR cluster. We recommend that you use the same VPC for your EMR cluster and the

RDS instance to save time for configuring a network connection. Otherwise, use Express Connect to configure a network connection.




### User-created database hosted on ECS

- Classic network

  The process for accessing a classic network user-created database and a classic network RDS instance is similar. Use the classic network for the EMR cluster to access the internal IP address of the user-created database. Make sure that the ECS instance on which the database is deployed and the instances of the EMR cluster are in the same security group. In the ECS console, choose Security Groups > Manage Instances > Add Instance.
- VPC

  The process for accessing a VPC user-created database and a VPC RDS instance is similar. Use a VPC for your EMR cluster. Make sure that the ECS instance where the database is deployed and the EMR cluster are in the same security group.

### On-premises database

You can assign an EIP address to your EMR cluster and access the public IP address of the database. Or, you can use Express Connect to connect the VPCs to access the database.

- Associate an EIP

  We recommend that you use a VPC EMR cluster if the on-premises database can be accessed over the public network. Create an EMR cluster in a VPC. Then, in the

ECS console, choose Manage > Configuration Information > More > Bind EIP and associate an EIP with each ECS instance. After the configurations, your cluster can access the public IP address of the on-premises database.

- Express Connect

  If the on-premises database is not allowed to be accessed over the public network, create an EMR cluster in a VPC and use Express Connect to connect the on-premises IDC and the VPC. For more information about Express Connect, see Express Connect.

# 16 Use E-MapReduce to submit a Spark Streaming job for consuming Kafka data

This topic describes how to create a Hadoop cluster and Kafka cluster by using E-MapReduce (EMR) and run a Spark Streaming job to consume Kafka data.

## Prerequisites

- You have registered an Alibaba Cloud account. For more information, see Create an Alibaba Cloud account.
- You have activated EMR.
- You have authorized the Alibaba Cloud account. For more information, see #unique_19.

## Context

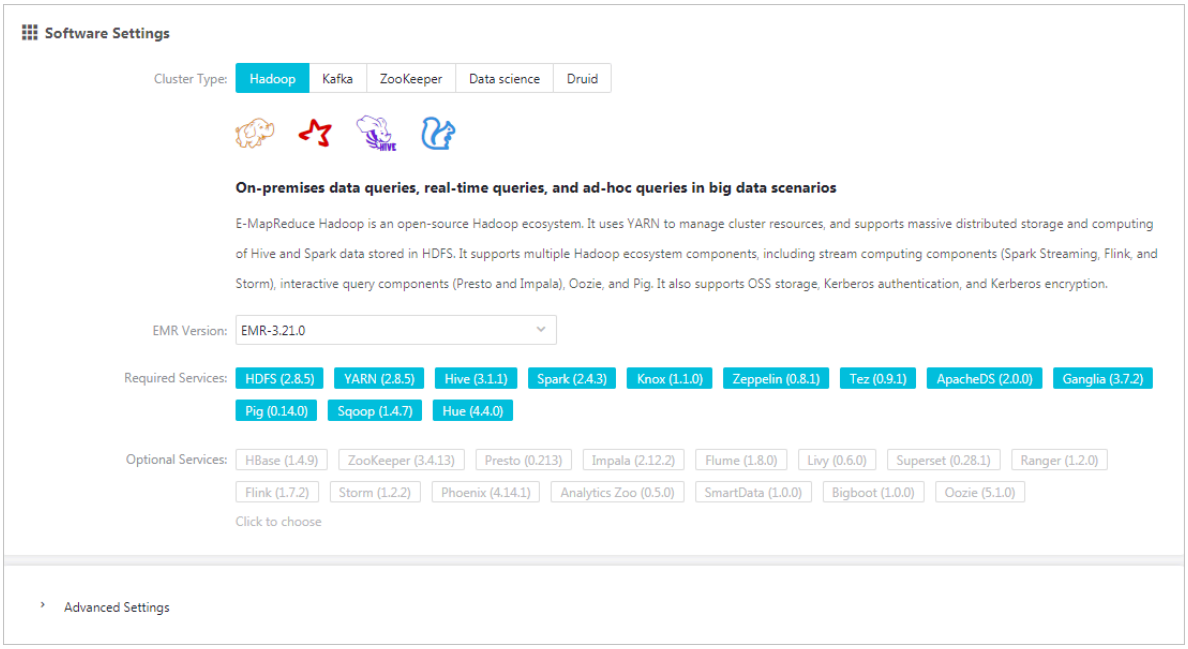
You always consume Kafka data in practical applications. In EMR, you can run a Spark Streaming job to consume Kafka data.

### Step 1: Create a Hadoop cluster and Kafka cluster

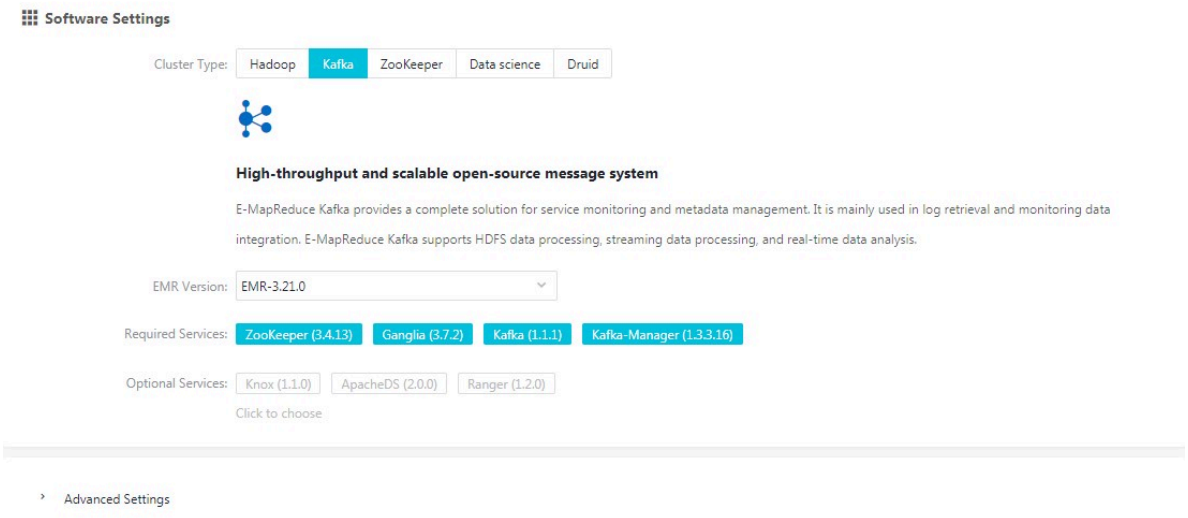
We recommend that you specify the same security group for the Hadoop cluster as that of the Kafka cluster when creating the two clusters. If the clusters are linked to different security groups, the two clusters are not accessible by each other. You must modify the required settings of the security groups to allow mutual access.

1. Log on to the Alibaba Cloud EMR console.

2. Create a Hadoop cluster. For more information, see Create a cluster.




3. Create a Kafka cluster. For more information, see Create a cluster.




### Step 2: Download a JAR file and upload it to the Hadoop cluster

In this example, the Demo project is customized and compiled to create a new JAR file. You need to upload the JAR file to the emr-header-1 instance of the Hadoop cluster.

1. Download the JAR file from this link.
2. Log on to the Alibaba Cloud EMR console.
3. On the Cluster Management tab, click the Cluster ID of the target cluster to enter the Hadoop cluster.

4. In the left-side navigation pane, select Instances and view the IP address of the emr-header-1 instance in the Hadoop cluster.
5. Log on to the emr-header-1 instance by using SSH.
6. Upload the JAR file to a directory of the emr-header-1 instance.

> Note:
> The `/ home / hadoop` directory is specified as a repository for data storage in this case. After you upload the JAR file, we recommend that you keep the logon window open for later use.

### Step 3: Create a topic on the Kafka cluster

You can create a topic in the EMR console. For more information, see #unique_34. You can also log on to the emr-header-1 instance and create a topic by using the CLI. In this example, you can create a topic named test with 10 partitions, 2 replicas.

1. Go to the Alibaba Cloud EMR console.
2. On the Cluster Management tab, click the Cluster ID of the target Kafka cluster to open the Details page of the cluster.
3. In the left-side navigation pane, select Instances and view the IP address of the emr-header-1 instance in the Kafka cluster.
4. Open a new shell in the SSH client and log on to the emr-header-1 instance in the new shell.
5. Use the following command to create a topic.

```
/ usr / lib / kafka - current / bin / kafka - topics . sh  --
 partitions   10  -- replicatio  n - factor   2  -- zookeeper   emr
 - header - 1 :/ kafka - 1 . 0 . 0  -- topic   test  -- create
```

> Note:
> After you create the topic, we recommend that you keep this logon window open for later use.

### Step 4: Run a Spark Streaming job

After performing the preceding steps, you can run a Spark Streaming job on the Hadoop cluster. The following is an example of running a job to count the number of words for a data stream.

1. Go to the logon window of the emr-header-1 instance in the Hadoop cluster.

   If you close the window, you need to log on again. For more information about the logon procedure, see Step 2: Download a JAR file and upload it to the Hadoop cluster.

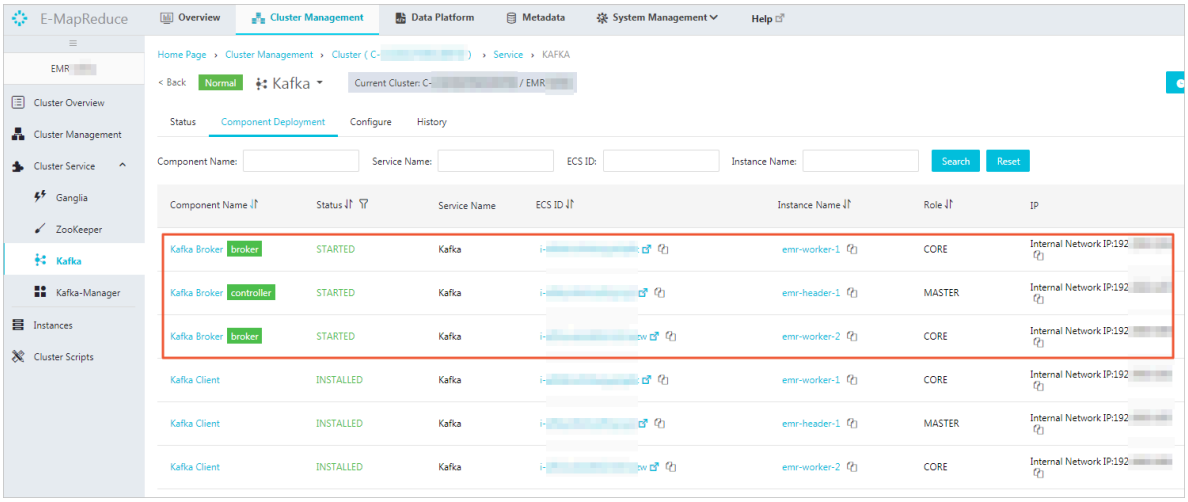
2. Use the following command to submit a job to the Kafka cluster for counting.

```
spark - submit  -- class   com . aliyun . emr . example . spark .
streaming . KafkaSampl  e   / home / hadoop / examples - 1 . 2 . 0
- shaded - 2 . jar   192 . 168 . xxx . xxx : 9092   test   5
```

   In the preceding command, the parameters after the name of the JAR file are described as follows:

   - 192.168.xxx.xxx: indicates the internal or public IP address of a broker in the Kafka cluster. Figure 16-1: List of components in the Kafka cluster shows an example.
   - test: indicates the name of the topic.
   - 5: indicates the time interval.

   Figure 16-1: List of components in the Kafka cluster




## Step 5: Use Kafka to publish messages

When you perform this step, ensure that the Spark Streaming job is running. After you start a Kafka producer, the number of words is displayed in a shell on a client instance of the Hadoop cluster. The value is updated in real time when you enter words into a shell on a client instance of the Kafka cluster.

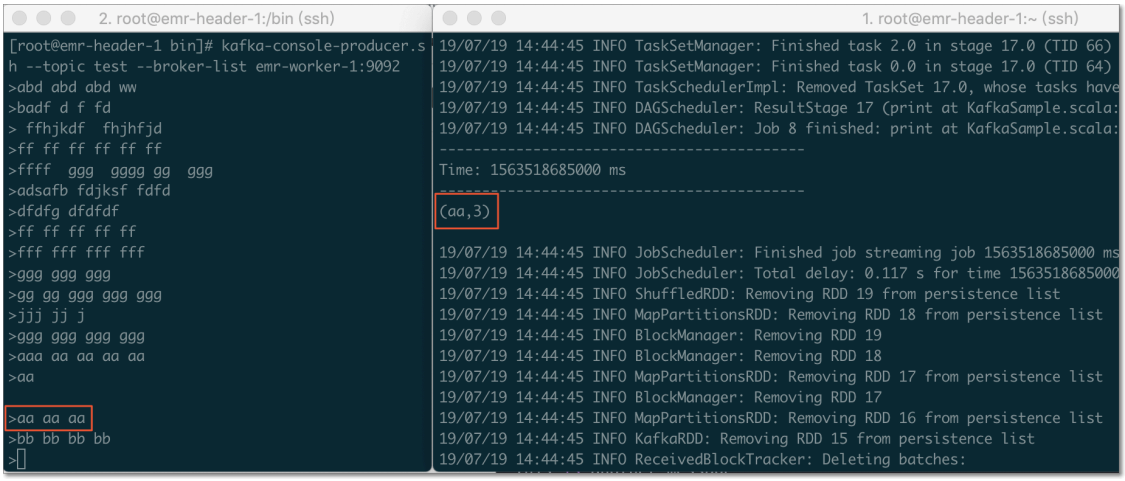
1. Go to the logon window of the emr-header-1 instance.

   If you close the window, you need to log on again. For more information about the logon procedure, see Step 3: Create a topic on the Kafka cluster.

2. In the logon window of the client instance in the Kafka cluster, use the following command to start a producer.

```
/ usr / lib / kafka - current / / bin / kafka - console - producer .
 sh  -- topic   test  -- broker - list   emr - worker - 1 : 9092
```

3. When you enter words in the Kafka logon window, the number of words is displayed and updated in the Hadoop logon window in real time.

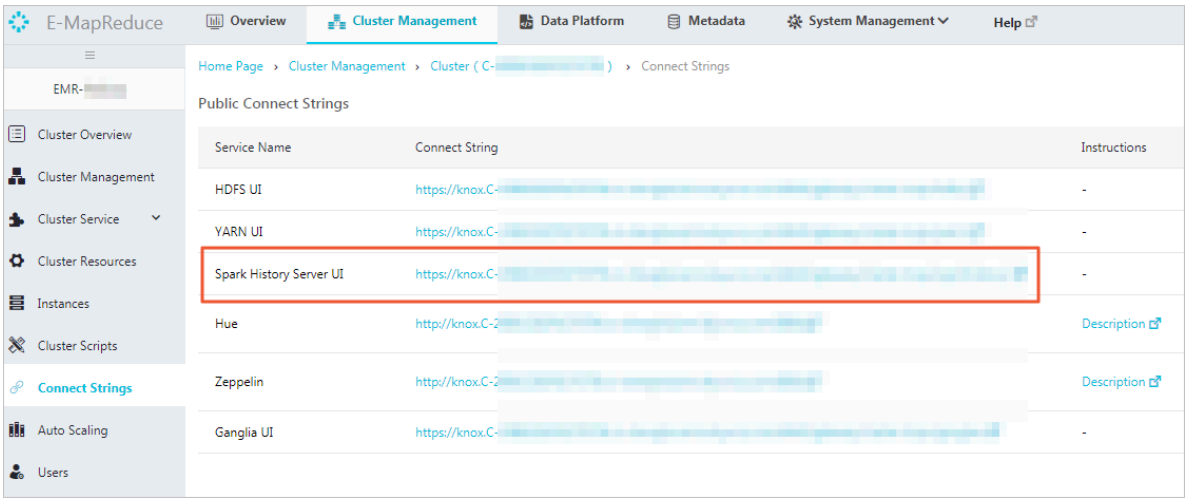


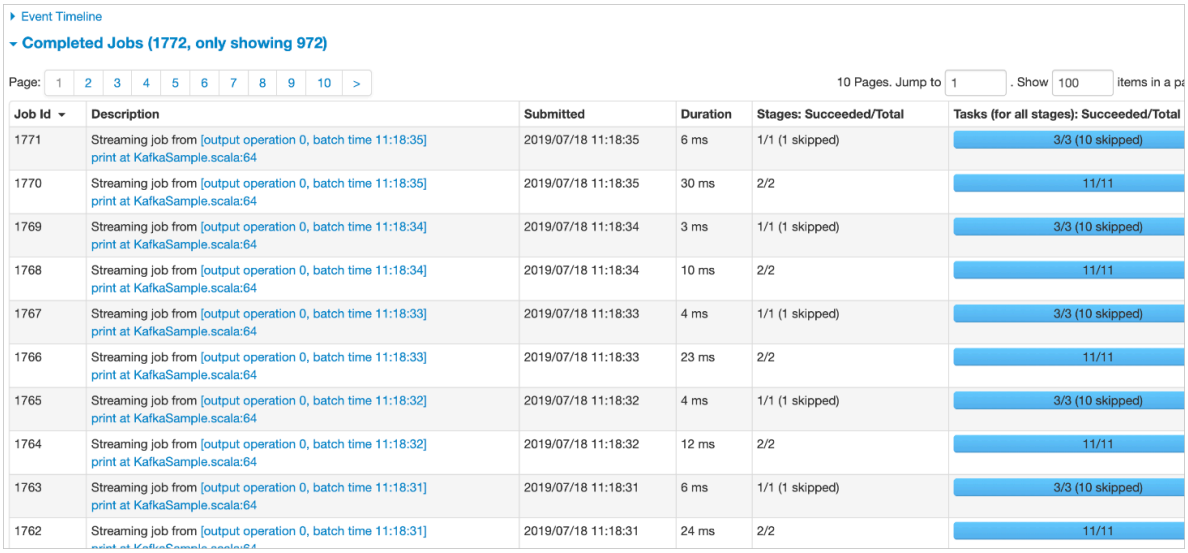

## Step 6: View the progress of the Spark Streaming job

After you run a Spark Streaming job, you can view the status of the job in the EMR console.

1. Go to the EMR console.

2. On the Connect Strings page, click the link next to the Spark History Server UI service name to view the status of the Spark Streaming job. For more information, see Access links and ports.



# 17 Use Kafka Connect to migrate data

During streaming data processing, data synchronization between Kafka and other systems or data migration between Kafka clusters is often required. This topic describes how to use Kafka Connect to migrate data between Kafka clusters.

## Prerequisites

- You have registered an Alibaba Cloud account. For more information, see Create an Alibaba Cloud account.
- You have activated E-MapReduce.
- You have authorized the Alibaba Cloud account. For more information, see Role authorization.

## Context

Kafka Connect is a scalable and reliable tool for fast transmitting streaming data between Kafka and other systems. For example, you can use Kafka Connect to obtain binlog data from a database and migrate the data of the database to a Kafka cluster. In this way, you can migrate the data of the database and indirectly connect the database to a downstream streaming data processing system. Kafka Connect also provides a Representational State Transfer (REST) application programming interface (API) to help you create and manage Kafka Connect connectors.

Kafka Connect can run in standalone or distributed mode. In standalone mode, all workers run in the same process. Compared with the standalone mode, the distributed mode is more scalable and fault-tolerant. It is the most commonly used mode and the recommended mode for the production environment.

This topic describes how to call the REST API of Kafka Connect to migrate data between Kafka clusters, where Kafka Connect runs in distributed mode.

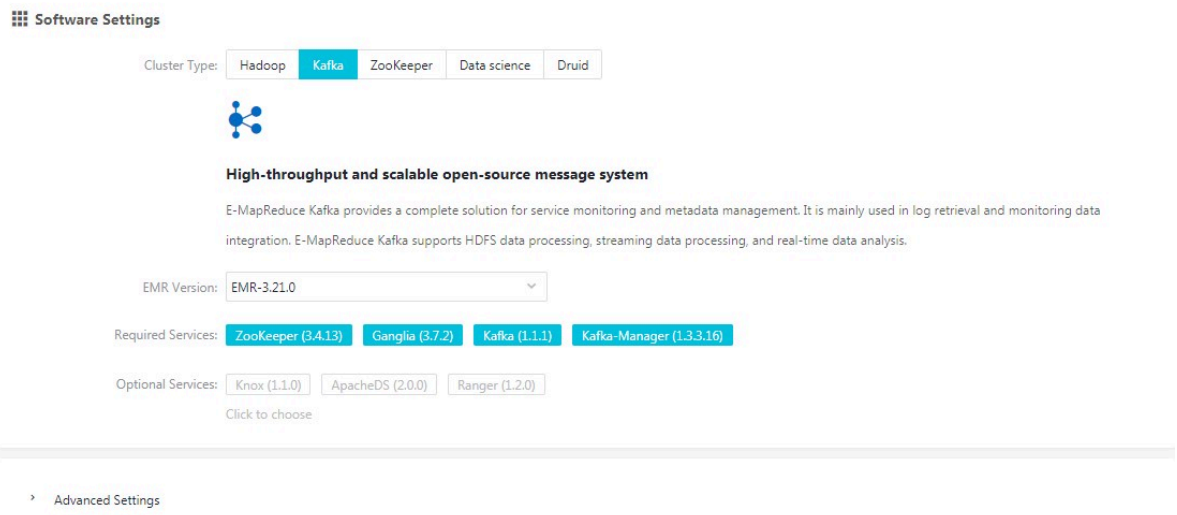
### Step 1: Create Kafka clusters

Create a source Kafka cluster and a target Kafka cluster in E-MapReduce. Kafka Connect is installed on the task node. Therefore, a task node must be created in the target Kafka cluster. Kafka Connect is started on the task node by default after the cluster is created. The port number is 8083.

We recommend that you add the source Kafka cluster and the target Kafka cluster to the same security group. If the source Kafka cluster and the target Kafka cluster belong to different security groups, the two clusters are not accessible to each other by default. You must modify the required settings of the security groups to allow mutual access.

1. Log on to the Alibaba Cloud E-MapReduce console.
2. Create the source Kafka cluster and the target Kafka cluster. For more information, see #unique_32.

> Note:
> When creating the target Kafka cluster, you must configure a task instance, that is, a task node.




### Step 2: Create a topic for storing the data to be migrated

Create a topic named connect in the source Kafka cluster.

1. Use Secure Shell (SSH) to log on to the header node of the source Kafka cluster. In this example, the header node is emr-header-1.

2. Run the following command as the root user to create a topic named connect:

```
kafka - topics . sh  -- create  -- zookeeper   emr - header - 1 :
2181  -- replicatio  n - factor   2  -- partitions   10  -- topic
connect
```


**Note:**
After performing the preceding operations, keep the logon window for later use.

### Step 3: Create a Kafka Connect connector

On the task node of the target Kafka cluster, run the `curl` command to create a Kafka Connect connector by using JavaScript Object Notation (JSON) data.

1. Use SSH to log on to the task node of the target Kafka cluster. In this example, the task node is emr-worker-3.
2. Optional: Customize Kafka Connect configuration.

   Go to the Configuration page of the Kafka service under the target Kafka cluster. Customize the offset.storage.topic, config.storage.topic, and status.storage.topic parameters in connect-distributed.properties. For more information, see #unique_36.

   Kafka Connect saves the offsets, configurations, and task status in the topics specified by the offset.storage.topic, config.storage.topic, and status.storage.topic parameters, respectively. Kafka Connect automatically creates these topics by using the default partition and replication factor that are saved in */ etc / ecm / kafka - conf / connect - distribute  d . properties .*
3. Run the following command as the root user to create a Kafka Connect connector:

```
curl  - X   POST  - H  " Content - Type :  applicatio  n / json "
-- data  '{" name ": " connect - test ", " config ": { " connector
. class ": " EMRReplica  torSourceC  onnector ", " key . converter
": " org . apache . kafka . connect . converters . ByteArrayC
onverter ", " value . converter ": " org . apache . kafka . connect
. converters . ByteArrayC  onverter ", " src . kafka . bootstrap
. servers ": "${ src - kafka - ip }: 9092 ", " src . zookeeper
. connect ": "${ src - kafka - curator - ip }: 2181 ", " dest .
zookeeper . connect ": "${ dest - kafka - curator - ip }: 2181 ",
" topic . whitelist ": "${ source - topic }", " topic . rename .
```

```
format ": "${ dest - topic }", " src . kafka . max . poll . records
": " 300 " } }'  http :// emr - worker - 3 : 8083 / connectors
```

In the JSON data, the `name` field indicates the name of the Kafka Connect connector to create, which is `connect - test` in this example. The `config` field needs to be configured based on your actual requirements. The following table describes the key variables of the config field.

| Variable | Description |
| --- | --- |
| ${source-topic} | The topics for storing the data to be migrated in the source Kafka cluster. For example, connect. Separate multiple topics with commas (,). |
| ${dest-topic} | The topics to which the data is migrated in the target Kafka cluster. For example, connect.replica. |
| ${src-kafka-curator-hostname} | The internal IP address of the node where the ZooKeeper service is installed in the source Kafka cluster. |
| ${dest-kafka-curator-hostname} | The internal IP address of the node where the ZooKeeper service is installed in the target Kafka cluster. |

Note:

After performing the preceding operations, keep the logon window for later use.

### Step 4: View the status of the Kafka Connect connector and task node

View the status of the Kafka Connect connector and task node and make sure that they are in normal status.

1. Return to the logon window on the task node of the target Kafka cluster. In the example, the task node is emr-worker-3.
2. Run the following command as the root user to view all Kafka Connect connectors:

```
curl   emr - worker - 3 : 8083 / connectors
```

```
[root@emr-worker-3 ~]# curl emr-worker-3:8083/connectors
["connect-test"][root@emr-worker-3 ~]#
```

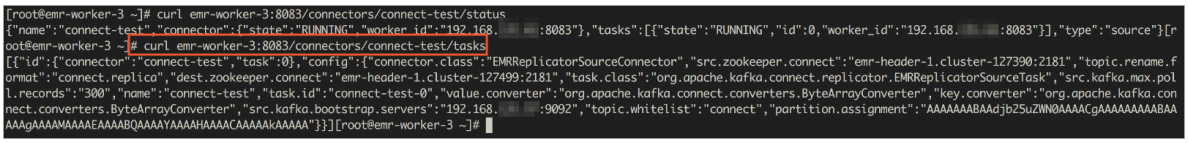
3. Run the following command as the root user to view the status of the Kafka Connect connector created in this example, that is, connect-test:

```
curl   emr - worker - 3 : 8083 / connectors / connect - test /
status
```


Make sure that the Kafka Connect connector (connect-test in this example) is in the RUNNING status.

4. Run the following command as the root user to view the details of the task node:

```
curl   emr - worker - 3 : 8083 / connectors / connect - test /
tasks
```



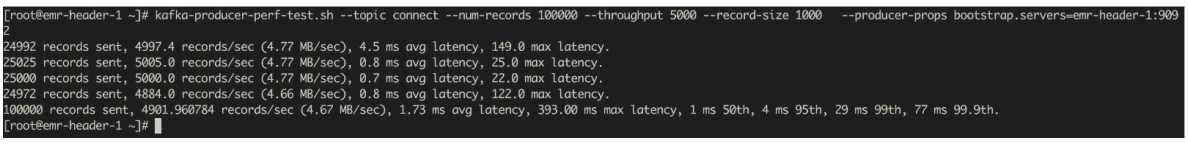

Make sure that no error message about the task node is returned.

### Step 5: Generate the data to be migrated

Send the data to be migrated to the connect topic in the source Kafka cluster.

1. Return to the logon window on the header node of the source Kafka cluster. In this example, the header node is emr-header-1.
2. Run the following command as the root user to send data to the connect topic:

```
kafka - producer - perf - test . sh  -- topic   connect  -- num -
records   100000  -- throughput   5000  -- record - size   1000  --
producer - props   bootstrap . servers = emr - header - 1 : 9092
```




### Step 6: View the result of data migration

After the data to be migrated is generated, Kafka Connect automatically migrates the data to the corresponding topic in the target Kafka cluster. In this example, the topic is connect.replica.

1. Return to the logon window on the task node of the target Kafka cluster. In this example, the task node is emr-worker-3.

2. Run the following command as the root user to check whether the data is migrated:

```
kafka - consumer - perf - test . sh  -- topic   connect . replica
-- broker - list   emr - header - 1 : 9092  -- messages   100000
```

```
[root@emr-worker-3 ~]# kafka-consumer-perf-test.sh  --topic connect.replica --broker-list emr-header-1:9092 --messages 1000000
start.time, end.time, data.consumed.in.MB, MB.sec, data.consumed.in.nMsg, nMsg.sec, rebalance.time.ms, fetch.time.ms, fetch.MB.sec, fetch.nMsg.sec
2019-07-22 10:13:17:855, 2019-07-22 10:13:32:055, 95.3674, 6.7160, 100000, 7042.2535, 3019, 11181, 8.5294, 8943.7439
[root@emr-worker-3 ~]#
```

According to the command output in the preceding figure, the 100,000 messages sent to the source Kafka cluster are migrated to the target Kafka cluster.

## Summary

This topic describes and demonstrates how to use Kafka Connect to migrate data between Kafka clusters. For more information about how to use Kafka Connect, see Kafka official website and REST API.