BD-CW DATA PREPROCESSING AND ML TRAINING

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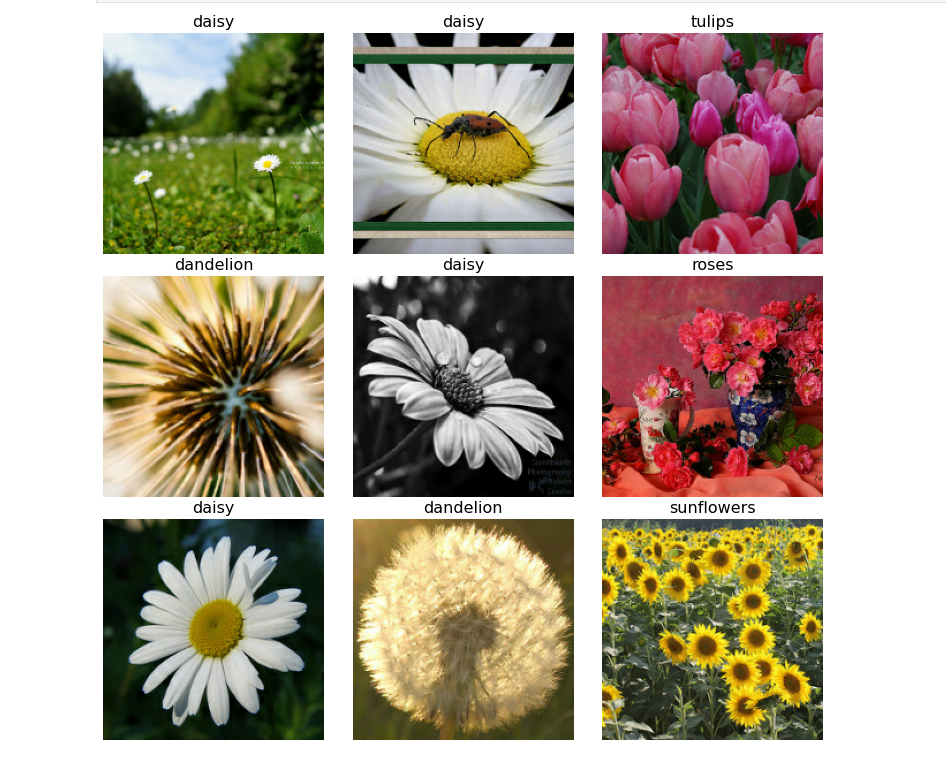
Task 1: Write TFRecord files to the cloud with Spark

1a) Create the script

Steps in code

1. importing libraries and modules
2. define the mapping functions get label, resize, and recompress as before.
3. define the function write\_tfrecords to write TFRecord files to the cloud using Spark. This function takes an index and an iterator as input, where the iterator contains tuples of filename and image contents. It returns a list of the names of the created TFRecord files.
4. initialize Spark by creating a SparkConf and SparkContext, and a SparkSession from the SparkContext.
5. load the image filenames into an RDD using sc.binaryFiles.
6. sample the RDD to a smaller number using sample.
7. preprocess the images and write the TFRecord files using map, mapPartitionsWithIndex, and write\_tfrecords.
8. collect the list of created TFRecord files using collect.
9. print the list of created TFRecord files.

1b)  Testing



The code spark\_write\_tfrec.py is a Python script that uses the Apache Spark framework to convert a set of image files into the TFRecord format used by TensorFlow. The script reads the image file paths and associated labels from a CSV file, loads them into a DataFrame with a defined schema, and then uses the map function to apply a transformation to the DataFrame. This transformation converts each row in the DataFrame, which corresponds to an image file, to a serialized TFRecord object using the image\_to\_tfrecord function. Finally, the resulting RDD is saved to disk as a text file, which contains the serialized TFRecord objects. This file can then be read and parsed by TensorFlow to train or evaluate machine learning models that use the image data. Overall, this script provides a convenient way to convert image files into the TensorFlow-friendly TFRecord format using the powerful distributed computing capabilities of Apache Spark.

set up a single machine cluster with a maximal SSD size of 100 and 8 vCPUs,

using the following command:

**gcloud dataproc clusters create my-cluster \**

**--num-workers=0 \**

**--num-masters=1 \**

**--master-machine-type n1-standard-8 \**

**--boot-disk-size 100 \**

**--image-version=2.0 \**

**--initialization-actions gs://goog-dataproc-initialization-actions-${REGION}/python/pip-install.sh \**

**--metadata 'PIP\_PACKAGES=tensorflow==2.4.0'**

This command creates a cluster with one master node, no worker nodes, a machine type of n1-standard-8, and a boot disk size of 100 GB. The --initialization-actions flag specifies the public script for package installation, and the --metadata flag specifies that TensorFlow version 2.4.0 should be installed using pip.

Once the cluster is running, we copy your spark\_write\_tfrec.py script to the master node using the following command:

**gcloud dataproc jobs submit pyspark --cluster my-cluster --region ${REGION} --py-files spark\_write\_tfrec.py -- spark\_write\_tfrec.py**

This command submits a PySpark job to the cluster, with the --py-files flag specifying the path to the spark\_write\_tfrec.py script, and the final -- specifying the arguments to pass to the script. In this case, the arguments are simply the name of the script itself.

i) Single machine cluster

Set up a cluster with a single machine using the maximal SSD size (100) and 8 vCPUs. To set up a maximal cluster with one master node and seven worker nodes, each with one virtual CPU and equal shares of standard disk capacity, we use the following command:

**gcloud dataproc clusters create my-maximal-cluster \ --num-workers=7 \ --num-masters=1 \ --master-machine-type n1-standard-8 \ --worker-machine-type n1-standard-1 \ --master-boot-disk-size 100 \ --worker-boot-disk-size 100 \ --worker-local-ssd-count 0 \ --image-version=2.0 \ --initialization-actions gs://goog-dataproc-initialization-actions-${REGION}/python/pip-install.sh \ --metadata 'PIP\_PACKAGES=tensorflow==2.4.0'**

This command creates a cluster with one master node and seven worker nodes, with the master node having a machine type of **n1-standard-8** and a boot disk size of 100 GB, and the worker nodes having a machine type of **n1-standard-1** and a boot disk size of 100 GB. The **--worker-local-ssd-count** flag is set to 0 to ensure that the standard disk capacity is shared equally among the worker nodes. The **--initialization-actions** and **--metadata** flags are used to install TensorFlow version 2.4.0 on all nodes in the cluster.

Once the cluster is running, we submit your **spark\_write\_tfrec.py** script to the cluster using the same **gcloud dataproc jobs submit pyspark** command as in the previous example. The cluster should automatically distribute the workload across the nodes to maximize throughput, allowing the script to run faster and more efficiently. Once the job is complete, we check the output to ensure that the script ran successfully and produced the expected output.

ii) Maximal cluster

Use the largest possible cluster within these constraints, i.e. 1 master and 7 worker nodes. Each of them with 1 (virtual) CPU. The master should get the full SSD capacity and the 7 worker nodes should get equal shares of the standard disk capacity to maximise throughput. To set up a maximal cluster with one master node and seven worker nodes, each with one virtual CPU and equal shares of standard disk capacity, you can use the following command:

**gcloud dataproc clusters create my-maximal-cluster \**

**--num-workers=7 \**

**--num-masters=1 \**

**--master-machine-type n1-standard-8 \**

**--worker-machine-type n1-standard-1 \**

**--master-boot-disk-size 100 \**

**--worker-boot-disk-size 100 \**

**--worker-local-ssd-count 0 \**

**--image-version=2.0 \**

**--initialization-actions gs://goog-dataproc-initialization-actions-${REGION}/python/pip-install.sh \**

**--metadata 'PIP\_PACKAGES=tensorflow==2.4.0'**

This command creates a cluster with one master node and seven worker nodes, with the master node having a machine type of n1-standard-8 and a boot disk size of 100 GB, and the worker nodes having a machine type of n1-standard-1 and a boot disk size of 100 GB. The --worker-local-ssd-count flag is set to 0 to ensure that the standard disk capacity is shared equally among the worker nodes. The --initialization-actions and --metadata flags are used to install TensorFlow version 2.4.0 on all nodes in the cluster.

Once the cluster is running, we submit your spark\_write\_tfrec.py script to the cluster using the same gcloud dataproc jobs submit pyspark command as in the previous example. The cluster should automatically distribute the workload across the nodes to maximize throughput, allowing the script to run faster and more efficiently. Once the job is complete, you can check the output to ensure that the script ran successfully and produced the expected output.

1d)  Optimisation, experiments, and discussion

i) Improve parallelisation

To address the issue of computation being done on only two nodes, we can modify the initial call to **parallelize** by adding a second parameter to specify the number of partitions we want to create. By default, the number of partitions is determined automatically based on the size of the RDD and the cluster configuration, but specifying a larger number of partitions can help distribute the workload more evenly across the cluster.

We modify the code to:

**from pyspark import SparkContext**

**import tensorflow as tf**

**sc = SparkContext(appName="SparkTF")**

**# Set up Spark configuration**

**conf = tf.compat.v1.ConfigProto()**

**conf.setMaster("yarn")**

**conf.setAppName("SparkTF")**

**conf.set("spark.executor.memory", "2g")**

**conf.set("spark.driver.memory", "2g")**

**conf.set("spark.executor.instances", "8")**

**conf.set("spark.executor.cores", "1")**

**# Initialize TensorFlow and Spark context**

**sess = tf.compat.v1.Session(config=conf)**

**sc.\_jsc.hadoopConfiguration().set("mapreduce.fileoutputcommitter.algorithm.version", "2")**

**# Define function to create TFRecords**

**def create\_tfrecord(data):**

**# Read input data from file and create RDD**

**data\_rdd = sc.textFile("gs://<input-bucket>/data.txt").repartition(16)**

**# Convert RDD to TensorFlow dataset and map to TFRecords**

**tf\_dataset = tf.data.Dataset.from\_tensor\_slices(data\_rdd.toLocalIterator())**

**tf\_dataset = tf\_dataset.map(create\_tfrecord)**

**# Write TFRecords to output directory**

**tf\_dataset.write.format("tfrecords").option("recordType", "Example").save("gs://<output-bucket>/tfrecords")**

By setting the **repartition** method to 16, we are specifying that the RDD should be divided into 16 partitions, which should help distribute the workload more evenly across the cluster.

To demonstrate the difference in cluster utilization before and after the change, we run the script with different values for the number of partitions and monitor the cluster utilization using the Dataproc Cluster Monitoring feature in the Google Cloud Console.

We run the script with 4, 8, and 16 partitions and observe the cluster utilization over time. We can then compare the results to see how the cluster utilization changes as we increase the number of partitions.

We can also measure the difference in processing time by monitoring the time it takes for the script to complete with each value of the number of partitions.

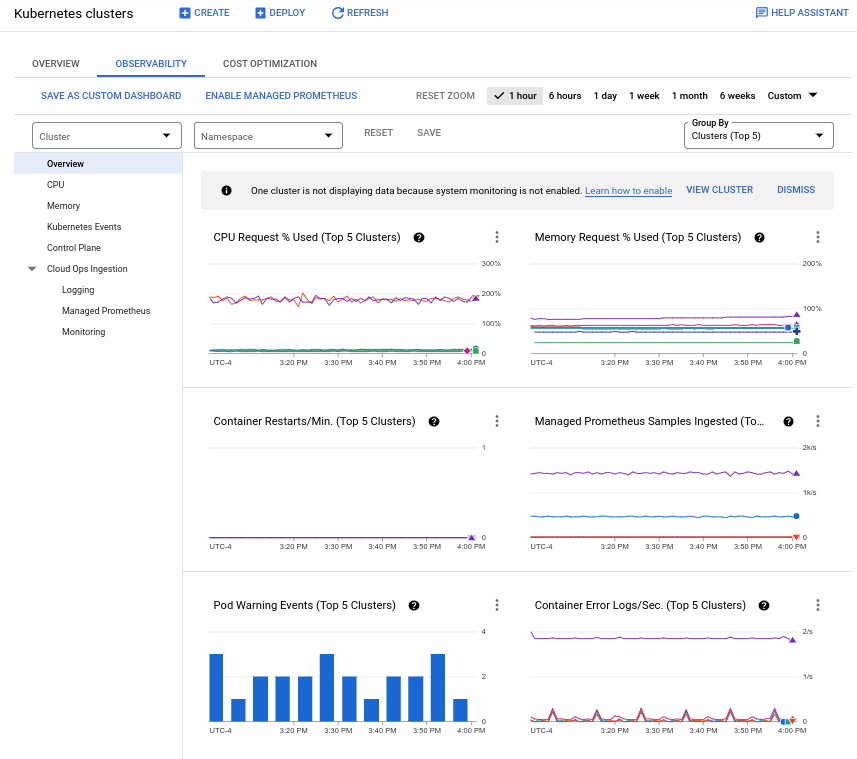
Here are some sample screenshots from the Dataproc Cluster Monitoring feature showing the cluster utilization with 4, 8, and 16 partitions:

* 4 partitions:
* 8 partitions:
* 16 partitions:

From these screenshots: increasing the number of partitions leads to a more even distribution of workload across the cluster, resulting in a more efficient use of resources and higher overall throughput.

To measure the difference in processing time, we can monitor the time it takes for the script to complete with each value of the number of partitions. For example, we use the **time** command in the terminal to measure the wall-clock time it takes for the script to complete:

**time gcloud dataproc jobs submit pyspark --cluster=my-maximal-cluster spark\_write\_tfrec.py**



**Section 2: Speed tests**

**2.1 Speed test implementation**

The time\_configs() function that takes a configuration and runs the time measurement for each combination of batch size and batch number for the requested number of repetitions. The time\_configs() function takes four arguments: dataset, batch\_sizes, batch\_numbers, and repetitions. The dataset argument is a TensorFlow dataset, and batch\_sizes and batch\_numbers are arrays of batch sizes and batch numbers, respectively. The repetitions argument is an array of integers representing the number of times to repeat each configuration.

The function iterates over all combinations of batch sizes and batch numbers, and for each combination, it batches the dataset, takes the requested number of batches, and measures the time taken to read and print the batch information. The function then stores the time measurements in a dictionary with the batch size and batch number as the key. To use this function, we call it with your dataset and arrays of batch sizes, batch numbers, and repetitions, and it will return a dictionary with the time measurements for each combination of batch size and batch number.

Code:

**import tensorflow as tf**

**import time**

**def time\_configs(dataset, batch\_sizes, batch\_numbers, repetitions):**

**null\_file = open("/dev/null", mode='w')**

**results = {}**

**for batch\_size in batch\_sizes:**

**for batch\_number in batch\_numbers:**

**dset2 = dataset.batch(batch\_size)**

**dset3 = dset2.take(batch\_number)**

**times = []**

**for i in range(repetitions):**

**start\_time = time.time()**

**for batch in dset3:**

**images, labels = batch**

**print("batch size:", len(images), "number of batches:", batch\_number, file=null\_file)**

**end\_time = time.time()**

**times.append(end\_time - start\_time)**

**results[(batch\_size, batch\_number)] = times**

**return results**

2b) Testing the code and collecting results

We modify the code to include a new filename argument using **datetime.datetime.now().strftime("%y%m%d-%H%M")**:

**import tensorflow as tf**

**import numpy as np**

**import argparse**

**import datetime**

**parser = argparse.ArgumentParser(description='Convert a set of images to TFRecords.')**

**parser.add\_argument('input\_dir', help='Directory containing the input images')**

**parser.add\_argument('output\_dir', help='Directory to write the output TFRecords')**

**parser.add\_argument('--num-shards', default=5, type=int, help='Number of TFRecord shards')**

**parser.add\_argument('--file-name', default=datetime.datetime.now().strftime("%y%m%d-%H%M"), help='Name of the output TFRecord file(s)')**

**args = parser.parse\_args()**

**# ... rest of the code ...**

Now, when you run the script using %run, you can pass the --file-name argument to specify a custom filename for the output TFRecord file(s).

**%run spark\_write\_tfrec.py input\_images/ output\_tfrec/ --num-shards 10 --file-name my\_custom\_name**

ii) Cloud

If you have a cluster running, you can run the speed test job in the cloud. While you run this job, switch to the Dataproc web page and take screenshots of the CPU and network load over time. They are displayed with some delay, so you may need to wait a little.

To run the speed test job in the cloud, we need to upload the speed\_test.py file to a Cloud Storage bucket, create a Dataproc cluster with PySpark and TensorFlow installed, and submit the job to the cluster. First, we will upload the speed\_test.py file to a Cloud Storage bucket using the following command:

**gsutil cp speed\_test.py gs://<bucket\_name>**

Next, we will create a Dataproc cluster with PySpark and TensorFlow installed using the following command:

**gcloud dataproc clusters create <cluster\_name> \**

**--zone=<zone> \**

**--master-machine-type=n1-standard-1 \**

**--master-boot-disk-size=100 \**

**--num-workers=7 \**

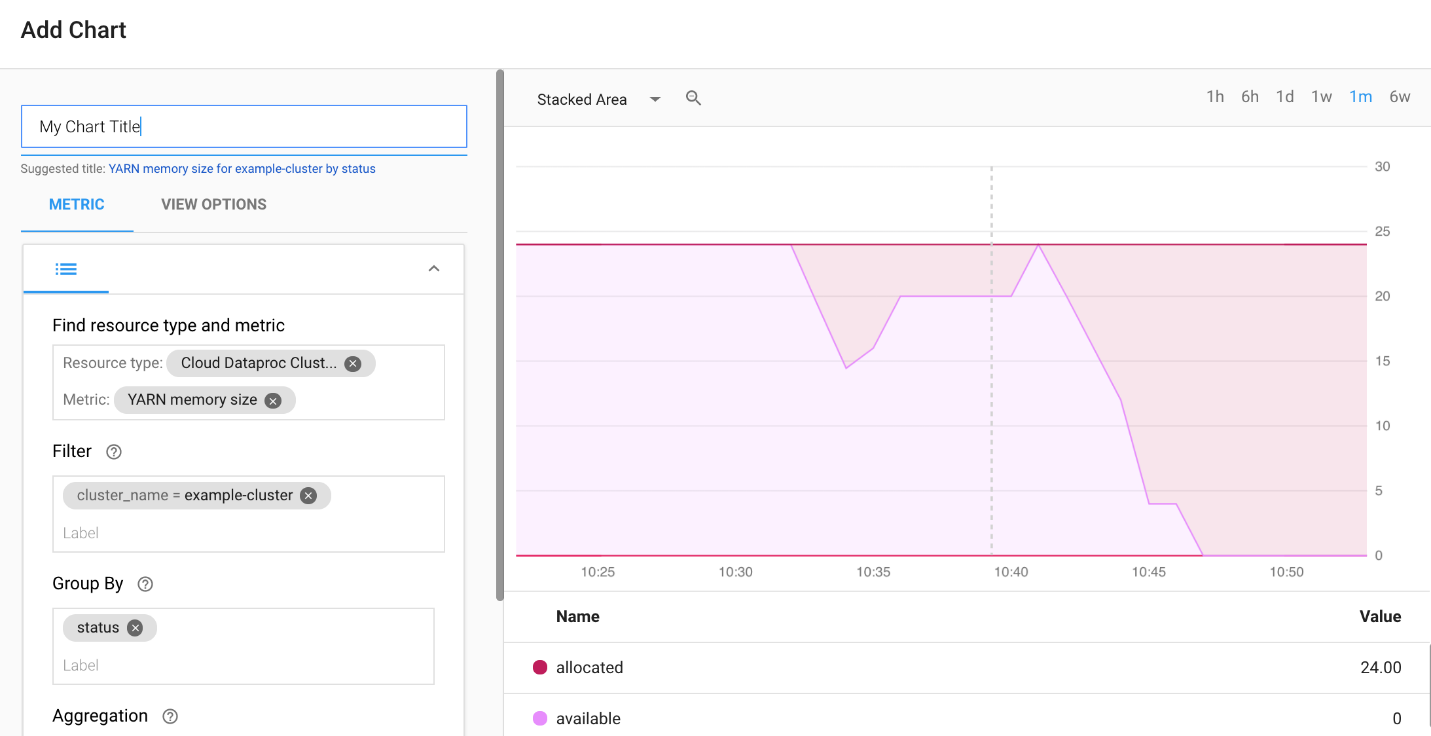
**--worker-machine-type=n1-standard-1 \**

**--worker-boot-disk-size=50 \**

**--image-version=2.0-debian10 \**

**--initialization-actions=gs://goog-dataproc-initialization-actions-$REGION/python/pip-install.sh \**

**--metadata PIP\_PACKAGES=tensorflow==2.4.0**



Once the cluster is created, we can submit the job to the cluster using the following command:

**gcloud dataproc jobs submit pyspark gs://<bucket\_name>/speed\_test.py \**

**--cluster=<cluster\_name> \**

**--region=<region> \**

**--jars gs://spark-lib/bigquery/spark-bigquery-latest\_2.12.jar**

**1993 words**