Serverless Data Processing with Dataflow - Writing an ETL Pipeline using Apache Beam and Cloud Dataflow (Python)

1 hour 30 minutes No cost

Overview

In this lab, you will learn how to:

- Build a batch Extract-Transform-Load pipeline in Apache Beam, which takes raw data from Google Cloud Storage and writes it to Google BigQuery.
- Run the Apache Beam pipeline on Cloud Dataflow.
- Parameterize the execution of the pipeline.

Prerequisites:

- Basic familiarity with Python.

Setup and requirements

For each lab, you get a new Google Cloud project and set of resources for a fixed time at no cost.

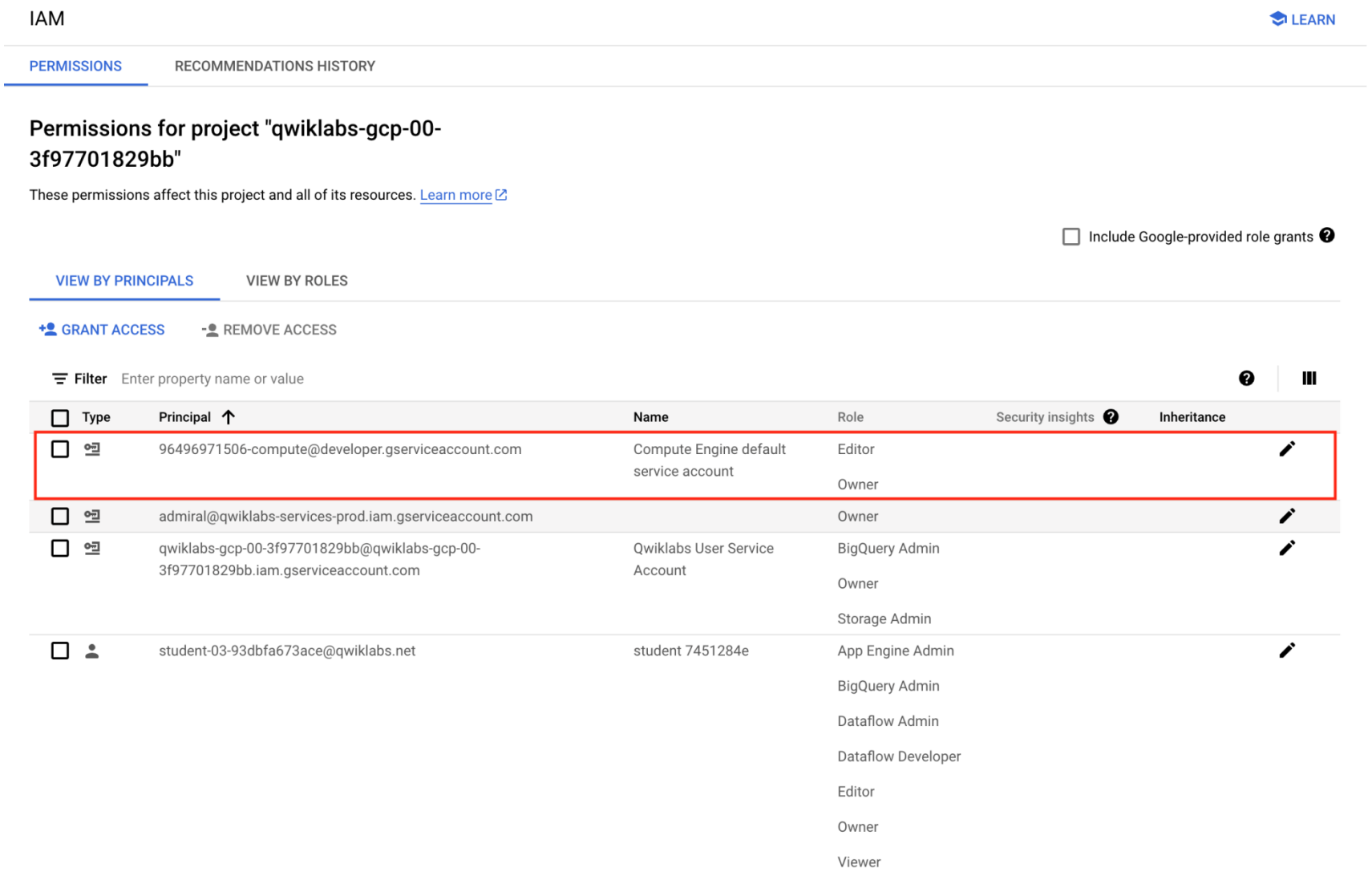
1. Sign in to Qwiklabs using an **incognito window**.
2. Note the lab's access time (for example, `1:15:00`), and make sure you can finish within that time.
   There is no pause feature. You can restart if needed, but you have to start at the beginning.
3. When ready, click **Start lab**.
4. Note your lab credentials (**Username** and **Password**). You will use them to sign in to the Google Cloud Console.
5. Click **Open Google Console**.
6. Click **Use another account** and copy/paste credentials for **this** lab into the prompts.
   If you use other credentials, you'll receive errors or **incur charges**.
7. Accept the terms and skip the recovery resource page.

Note: Do not click **End Lab** unless you have finished the lab or want to restart it. This clears your work and removes the project.

Check project permissions

Before you begin your work on Google Cloud, you need to ensure that your project has the correct permissions within Identity and Access Management (IAM).

1. In the Google Cloud console, on the **Navigation menu** (☰), select **IAM & Admin** > **IAM**.
2. Confirm that the default compute Service Account `{project-number}-compute@developer.gserviceaccount.com` is present and has the `editor` role assigned. The account prefix is the project number, which you can find on **Navigation menu** > **Cloud Overview** > **Dashboard**.



Note: If the account is not present in IAM or does not have the `editor` role, follow the steps below to assign the required role.

1. In the Google Cloud console, on the **Navigation menu**, click **Cloud Overview > Dashboard**.
2. Copy the project number (e.g. `729328892908`).
3. On the **Navigation menu**, select **IAM & Admin** > **IAM**.
4. At the top of the roles table, below **View by Principals**, click **Grant Access**.
5. For **New principals**, type:

{project-number}-compute@developer.gserviceaccount.com

6. Replace `{project-number}` with your project number.
7. For **Role**, select **Project** (or Basic) > **Editor**.
8. Click **Save**.

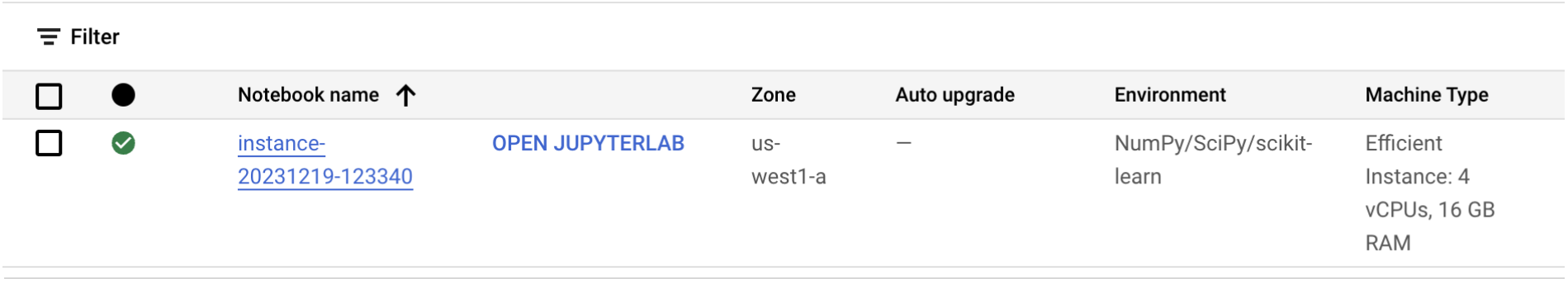
Jupyter notebook-based development environment setup

For this lab, you will be running all commands in a terminal from your notebook.

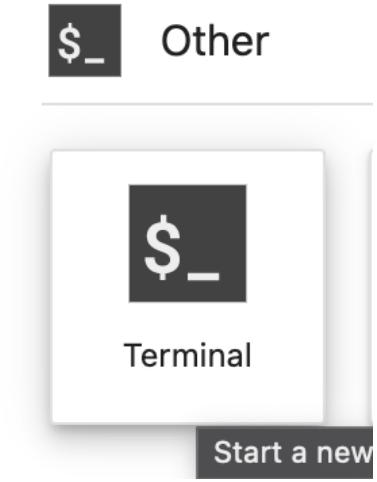
1. In the Google Cloud Console, on the **Navigation Menu**, click **Vertex AI > Workbench**.
2. Enable **Notebooks API**.
3. On the Workbench page, click **CREATE NEW**.
4. In the **New instance** dialog box that appears, set the region to and zone to .
5. For Environment, select **Apache Beam**.
6. Click **CREATE** at the bottom of the dialog vox.

Note: The environment may take 3 - 5 minutes to be fully provisioned. Please wait until the step is complete. **Note:** Click **Enable Notebook API** to enable the notebook api.

7. Once the environment is ready, click the **OPEN JUPYTERLAB** link next to your Notebook name. This will open up your environment in a new tab in your browser.



8. Next, click **Terminal**. This will open up a terminal where you can run all the commands in this lab.



Download Code Repository

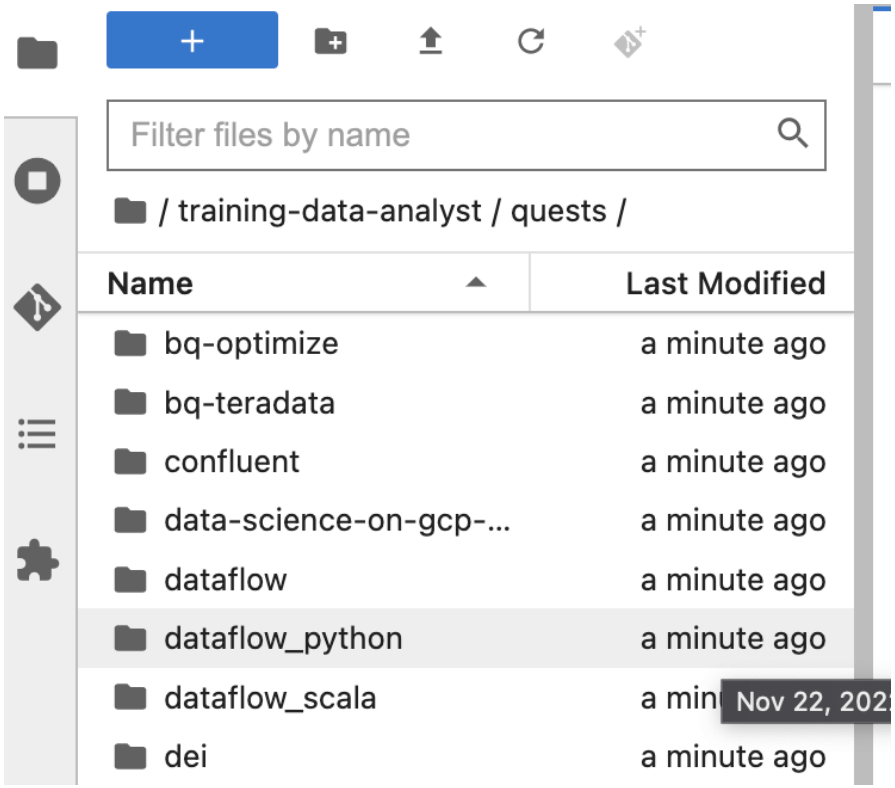
Next you will download a code repository for use in this lab.

1. In the terminal you just opened, enter the following:

```
git clone https://github.com/GoogleCloudPlatform/training-data-analyst cd /home/jupyter/training-data-analyst/quests/dataflow_python/
```

2. On the left panel of your notebook environment, in the file browser, you will notice the **training-data-analyst** repo added.

3. Navigate into the cloned repo `/training-data-analyst/quests/dataflow_python/`. You will see a folder for each lab, which is further divided into a `lab` sub-folder with code to be completed by you, and a `solution` sub-folder with a fully workable example to reference if you get stuck.



Note: To open a file for editing purposes, simply navigate to the file and click on it. This will open the file, where you can add or modify code.

Click **Check my progress** to verify the objective. Create notebook instance and clone course repo

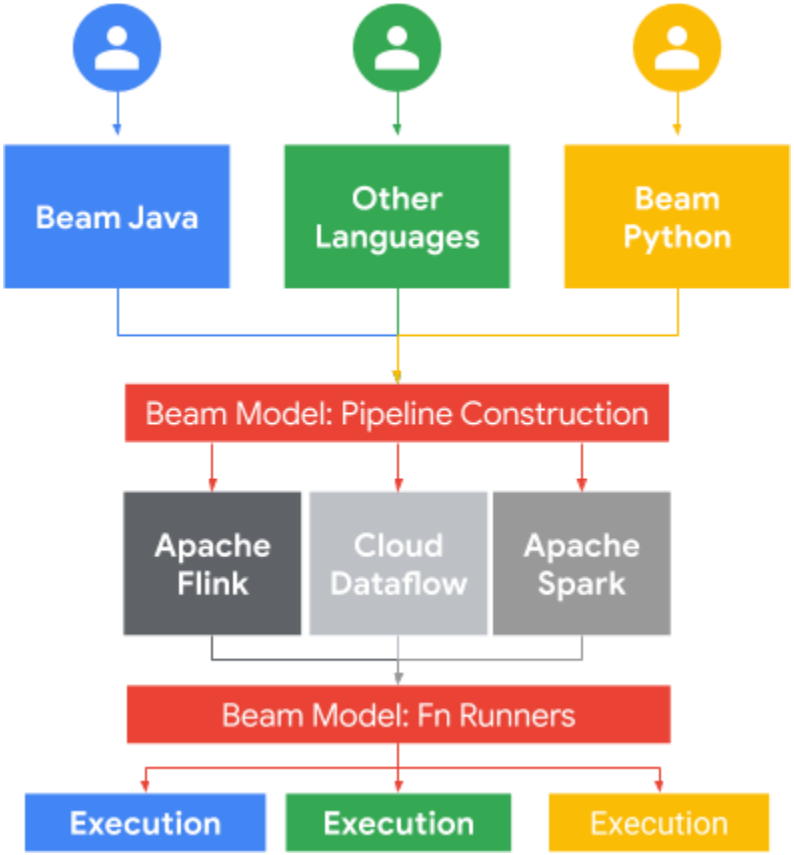
Apache Beam and Cloud Dataflow

About 5 minutes

Cloud Dataflow is a fully-managed Google Cloud Platform service for running batch and streaming Apache Beam data processing pipelines.

Apache Beam is an open source, advanced, unified, and portable data processing programming model that allows end users to define both batch and streaming data-parallel processing pipelines using Java, Python, or Go. Apache Beam pipelines can be executed on your local development machine

on small datasets, and at scale on Cloud Dataflow. However, because Apache Beam is open source, other runners exist — you can run Beam pipelines on Apache Flink and Apache Spark, among others.



Lab part 1. Writing an ETL pipeline from scratch

Introduction

In this section, you write an Apache Beam Extract-Transform-Load (ETL) pipeline from scratch.

Dataset and use case review

For each lab in this quest, the input data is intended to resemble web server logs in Common Log format along with other data that a web server might contain. For this first lab, the data is treated as a batch source; in later labs, the data will be treated as a streaming source. Your task is to read the data, parse it, and then write it to BigQuery, a serverless data warehouse, for later data analysis.

Open the appropriate lab

- Return to the terminal in your IDE, and copy and paste the following command:

cd 1_Basic_ETL/lab export BASE_DIR=$(pwd)

Set up the virtual environment and dependencies

Before you can begin editing the actual pipeline code, you need to ensure that you have installed the necessary dependencies.

1. In the terminal, create a virtual environment for your work in this lab:

sudo apt-get update && sudo apt-get install -y python3-venv python3 -m venv df-env source df-env/bin/activate

2. Next, install the packages you will need to execute your pipeline:

python3 -m pip install -q --upgrade pip setuptools wheel python3 -m pip install apache-beam[gcp]

3. Finally, ensure that the Dataflow API is enabled:

gcloud services enable dataflow.googleapis.com

Write your first pipeline

1 hour

Task 1. Generate synthetic data

1. Run the following command in the terminal to clone a repository containing scripts for generating synthetic web server logs:

cd $BASE_DIR/../.. source create_batch_sinks.sh bash generate_batch_events.sh head events.json

The script creates a file called `events.json` containing lines resembling the following:

{"user_id": "-6434255326544341291", "ip": "192.175.49.116", "timestamp": "2019-06-19T16:06:45.118306Z", "http_request": "\"GET eucharya.html HTTP/1.0\"", "lat": 37.751, "lng": -97.822, "http_response": 200, "user_agent": "Mozilla/5.0 (compatible; MSIE 7.0; Windows NT 5.01; Trident/5.1)", "num_bytes": 182}

It then automatically copies this file to your Google Cloud Storage bucket at .

2. In another browser tab, navigate to Google Cloud Storage and confirm that your storage bucket contains a file called `events.json`.

Click **Check my progress** to verify the objective. Generate synthetic data

Task 2. Read data from your source

If you get stuck in this or later sections, you can refer to the solution.

1. In your file explorer, navigate to the lab folder `1_Basic_ETL/lab` and click **my_pipeline.py**. This will open the file in an editor panel. Make sure the following packages are imported:

import argparse import time import logging import json import apache_beam as beam from apache_beam.options.pipeline_options import GoogleCloudOptions from apache_beam.options.pipeline_options import PipelineOptions from apache_beam.options.pipeline_options import StandardOptions from apache_beam.runners import DataflowRunner, DirectRunner

2. Scroll down to the `run()` method. This method currently contains a pipeline that doesn't do anything; note how a Pipeline object is created using a PipelineOptions object and the final line of the method runs the pipeline:

options = PipelineOptions() # Set options p = beam.Pipeline(options=options) # Do stuff p.run()

- All data in Apache Beam pipelines reside in PCollections. To create your pipeline's initial `PCollection`, you will need to apply a root transform to your pipeline object. A root transform creates a `PCollection` from either an external data source or some local data you specify.
- There are two kinds of root transforms in the Beam SDKs: **Read** and **Create**. **Read** transforms read data from an external source, such as a text file or a database table. **Create** transforms create a `PCollection` from an in-memory `list` and are especially useful for testing.

The following example code shows how to apply a `ReadFromText` root transform to read data from a text file. The transform is applied to a `Pipeline` object, `p`, and returns a pipeline dataset in the form of a `PCollection[str]` (using notation coming from parameterized type hints). *"ReadLines"* is your name for the transform, which will be helpful later when working with larger pipelines.

lines = p | "ReadLines" >> beam.io.ReadFromText("gs://path/to/input.txt")

3. Inside the `run()` method, create a string constant called *"input"* and set its value to `gs://<YOUR-PROJECT-ID>/events.json`. In a future lab, you will use command-line parameters to pass this information.
4. Create a `PCollection` of strings of all the events in `events.json` by calling the `textio.ReadFromText` transform.
5. Add any appropriate import statements to the top of `my_pipeline.py`.
6. To save your work, click on **File** and select **Save** in the top navigation menu.

Task 3. Run your pipeline to verify that it works

- Return to the terminal, and return to the `$BASE_DIR` folder and execute the following commands. Be sure to set the `PROJECT_ID` environment variable before running the pipeline:

cd $BASE_DIR # Set up environment variables export PROJECT_ID=$(gcloud config get-value project) # Run the pipeline python3 my_pipeline.py \ --project=${PROJECT_ID} \ --region={{{project_0.startup_script.lab_region|Region}}} \ --stagingLocation=gs://$PROJECT_ID/staging/ \ --tempLocation=gs://$PROJECT_ID/temp/ \ --runner=DirectRunner

At the moment, your pipeline doesn't actually do anything; it simply reads in data.

However, running it demonstrates a useful workflow, in which you verify the pipeline locally and cheaply using DirectRunner running on your local machine before doing more expensive computations. To run the pipeline using Google Cloud Dataflow, you may change `runner` to DataflowRunner.

Task 4. Add in a transformation

If you get stuck, refer to the solution.

Transforms are what change your data. In Apache Beam, transforms are done by the PTransform class. At runtime, these operations will be performed on a number of independent workers.

The input and output to every `PTransform` is a `PCollection`. In fact, though you may not have realized it, you have already used a `PTransform` when you read in data from Google Cloud Storage. Whether or not you assigned it to a variable, this created a `PCollection` of strings.

Because Beam uses a generic apply method for `PCollection`s, represented by the pipe operator `|` in Python, you can chain transforms sequentially. For example, you can chain transforms to create a sequential pipeline, like this one:

[Output_PCollection] = ([Input_PCollection] | [First Transform] | [Second Transform] | [Third Transform])

For this task, you will use a new sort of transform, a ParDo. `ParDo` is a Beam transform for generic parallel processing.

The `ParDo` processing paradigm is similar to the "Map" phase of a Map/Shuffle/Reduce-style algorithm: a `ParDo` transform considers each element in the input `PCollection`, performs some processing function (your user code) on that element, and emits zero, one, or multiple elements to an output `PCollection`.

`ParDo` is useful for a variety of common data processing operations, however there are special `PTransform`s in Python to make the process simpler, including:

- **Filtering a dataset.** You can use `Filter` to consider each element in a `PCollection` and either output that element to a new `PCollection`, or discard it depending on the output of a Python callable which returns a boolean value.
- **Formatting or type-converting each element in a dataset.** If your input `PCollection` contains elements that are of a different type or format than you want, you can use `Map` to perform a conversion on each element and output the result to a new `PCollection`.
- **Extracting parts of each element in a dataset.** If you have a `PCollection` of records with multiple fields, for example, you can also use `Map` or `FlatMap` to parse out just the fields you want to consider into a new `PCollection`.
- **Performing computations on each element in a dataset.** You can use `ParDo`, `Map`, or `FlatMap` to perform simple or complex computations on every element, or certain elements, of a `PCollection` and output the results as a new `PCollection`.

To complete this task, you need to write a `Map` transform that reads in a JSON string representing a single event, parses it using the Python `json` package, and outputs the dictionary returned by `json.loads`.

`Map` functions can be implemented in two ways, either *inline* or via a *predefined callable*. You write inline `Map` functions like this:

p | beam.Map(lambda x : something(x))

Alternatively, `beam.Map` can be used with a Python callable defined earlier in the script:

def something(x): y = # Do something! return y p | beam.Map(something)

If you need more flexibility, than `beam.Map` (and other lightweight `DoFn`s) offers, then you can implement `ParDo` with custom `DoFn`s that subclass DoFn. This allows them to be more easily integrated with testing frameworks.

class MyDoFn(beam.DoFn): def process(self, element): output = #Do Something! yield output p | beam.ParDo(MyDoFn())

Remember, if you get stuck, refer to the solution.

Task 5. Write to a sink

At this point, your pipeline reads a file from Google Cloud Storage, parses each line, and emits a Python dictionary for each element. The next step is to write these objects into a BigQuery table.

1. While you can instruct your pipeline to create a BigQuery table if needed, you will need to create the dataset ahead of time. This has already been done by the `generate_batch_events.sh` script. You can examine the dataset using the following code:

Examine dataset bq ls # No tables yet bq ls logs

To output your pipeline's final `PCollection`s, you apply a *Write* transform to that `PCollection`. *Write* transforms can output the elements of a `PCollection` to an external data sink, such as a database table. You can use *Write* to output a `PCollection` at any time in your pipeline, although you'll typically write out data at the end of your pipeline.

The following example code shows how to apply a `WriteToText` transform to write a `PCollection` of string to a text file:

p | "WriteMyFile" >> beam.io.WriteToText("gs://path/to/output")

2. In this case, instead of using `WriteToText`, use `WriteToBigQuery`.

This function requires a number of things to be specified, including the specific table to write to and the schema of this table. You can optionally specify whether to append to an existing table, recreate existing tables (helpful in early pipeline iteration), or create the table if it doesn't exist. By default, this transform *will* create tables that don't exist and *won't* write to a non-empty table.

3. However, we do need to specify our schema. There are two ways to do this. We can specify the schema as a single string or in JSON format. For example, suppose our dictionary has three fields: name (of type `str`), ID (of type `int`) and balance (of type `float`). Then we can specify the schema in a single line:

table_schema = 'name:STRING,id:INTEGER,balance:FLOAT'

Or specify it as JSON:

table_schema = { "fields": [{ "name": "name", "type": "STRING" }, { "name": "id", "type": "INTEGER", "mode": "REQUIRED" }, { "name": "balance", "type": "FLOAT", "mode": "REQUIRED" }] }

In the first case (the single string), all fields are assumed to be `NULLABLE`. We can specify the mode if we use the JSON approach instead.

4. Once we have defined the table schema, then we can add the sink to our DAG:

p | 'WriteToBQ' >> beam.io.WriteToBigQuery('project:dataset.table', schema=table_schema, create_disposition=beam.io.BigQueryDisposition.CREATE_IF_NEEDED, write_disposition=beam.io.BigQueryDisposition.WRITE_TRUNCATE)
Note: `WRITE_TRUNCATE` will delete and recreate your table each and every time. This is helpful in early pipeline iteration, especially as you are iterating on your schema, but can easily cause unintended issues in production. `WRITE_APPEND` or `WRITE_EMPTY` are safer.

Remember to define the table schema **and** add the BigQuery sink to your pipeline. Remember, if you get stuck, refer to the solution.

Task 6. Run your pipeline

1. Return to the terminal, and run your pipeline using almost the same command as earlier. However, now use the `DataflowRunner` to run the pipeline on Cloud Dataflow.

Set up environment variables cd $BASE_DIR export PROJECT_ID=$(gcloud config get-value project) # Run the pipelines python3 my_pipeline.py \ --project=${PROJECT_ID} \ --region={{{project_0.startup_script.lab_region|Region}}} \ --stagingLocation=gs://$PROJECT_ID/staging/ \ --tempLocation=gs://$PROJECT_ID/temp/ \ --runner=DataflowRunner

The overall shape should be a single path, starting with the `Read` transform and ending with the `Write` transform. As your pipeline runs, workers will be added automatically, as the service determines the needs of your pipeline, and then disappear when they are no longer needed. You can observe this by navigating to Compute Engine, where you should see virtual machines created by the Dataflow service.

Note: If your pipeline is building successfully, but you're seeing a lot of errors due to code or misconfiguration in the Dataflow service, you can set `runner` back to `DirectRunner` to run it locally and receive faster feedback. This approach works in this case because the dataset is small and you are not using any features that aren't supported by `DirectRunner`.

2. Once your pipeline has finished, return to the BigQuery browser window and query your table.

If your code isn’t performing as expected and you don’t know what to do, check out the solution.

Click **Check my progress** to verify the objective. Run your pipeline

Lab part 2. Parameterizing basic ETL

Approximately 20 minutes

Much of the work of data engineers is either predictable, like recurring jobs, or it’s similar to other work. However, the process for running pipelines requires engineering expertise. Think back to the steps that you just completed:

1. You created a development environment and developed a pipeline. The environment included the Apache Beam SDK and other dependencies.
2. You executed the pipeline from the development environment. The Apache Beam SDK staged files in Cloud Storage, created a job request file, and submitted the file to the Cloud Dataflow service.

It would be much better if there were a way to initiate a job through an API call or without having to set up a development environment (which non-technical users would be unable to do). This would also allow you to run pipelines.

Dataflow Templates seek to solve this problem by changing the representation that is created when a pipeline is compiled so that it is parameterizable. Unfortunately, it is not as simple as exposing command-line parameters, although that is something you do in a later lab. With Dataflow Templates, the workflow above becomes:

1. Developers create a development environment and develop their pipeline. The environment includes the Apache Beam SDK and other dependencies.
2. Developers execute the pipeline and create a template. The Apache Beam SDK stages files in Cloud Storage, creates a template file (similar to job request), and saves the template file in Cloud Storage.
3. Non-developer users or other workflow tools like Airflow can easily execute jobs with the Google Cloud Console, gcloud command-line tool, or the REST API to submit template file execution requests to the Cloud Dataflow service.

In this lab, you will practice using one of the many Google-created Dataflow Templates to accomplish the same task as the pipeline that you built in Part 1.

Task 1. Create a JSON schema file

Just like before, you must pass the Dataflow Template a JSON file representing the schema in this example.

1. Return to the terminal in your IDE. Run the following commands to navigate back to the main directory, then grab the schema from your existing `logs.logs` table:

cd $BASE_DIR/../.. bq show --schema --format=prettyjson logs.logs

2. Now, capture this output in a file and upload to GCS. The extra `sed` commands are to build a full JSON object that Dataflow will expect.

bq show --schema --format=prettyjson logs.logs | sed '1s/^/{"BigQuery Schema":/' | sed '$s/$/}/' > schema.json cat schema.json export PROJECT_ID=$(gcloud config get-value project) gsutil cp schema.json gs://${PROJECT_ID}/

Click **Check my progress** to verify the objective. Creating a JSON schema file

Task 2. Write a JavaScript user-defined function

The Cloud Storage to BigQuery Dataflow Template requires a JavaScript function to convert the raw text into valid JSON. In this case, each line of text is valid JSON, so the function is somewhat trivial.

1. To complete this task, create a **New File** in the **dataflow_python** folder in the file explorer of your IDE.
2. To create **New File**, click on **File >> New >> Text File**.

3. Rename the file name as **transform.js**, to rename the file name right click on it.
4. Open **transform.js file** in the editor panel, click on the file to open it.
5. Copy the function below to the transform.js file and save it:

```
function transform(line) { return line; }
```

6. Then run the following to copy the file to Google Cloud Storage:

```
export PROJECT_ID=$(gcloud config get-value project) gsutil cp *.js gs://${PROJECT_ID}/
```

Click **Check my progress** to verify the objective. Write a JavaScript user-defined function in Javascript file

Task 3. Run a Dataflow Template

1. Go to the Cloud Dataflow Web UI.
2. Click **CREATE JOB FROM TEMPLATE**.
3. Enter a Job name for your Cloud Dataflow job.
4. Under **Dataflow template**, select the **Text Files on Cloud Storage to BigQuery** template under the **Process Data in Bulk (batch)** section, NOT the Streaming section.
5. Under **Cloud Storage Input File**, enter the path to `events.json` in the form
6. Under **Cloud Storage location of your BigQuery schema file**, write the path to your `schema.json` file, in the form
7. Under **BigQuery output table**, enter
8. Under **Temporary BigQuery directory**, enter a new folder within this same bucket. The job will create it for you.
9. Under **Temporary location**, enter a second new folder within this same bucket.
10. Leave **Encryption** at **Google-managed encryption key**.
11. Click to open **Optional Prameters**.
12. Under **JavaScript UDF path in Cloud Storage**, enter in the path to your `.js`, in the form
13. Under **JavaScript UDF name**, enter `transform`.
14. Click the **Run job** button.

While your job is running, you may inspect it from within the Dataflow Web UI.

Click **Check my progress** to verify the objective. Running a Dataflow Template

Task 4. Inspect the Dataflow Template code

The code for the Dataflow Template you just used is located in this TextIOToBigQuery guide.

- Scroll down to the main method. The code should look familiar to the pipeline you authored!
  - It begins with a `Pipeline` object, created using a `PipelineOptions` object.
  - It consists of a chain of `PTransform`s, beginning with a TextIO.read() transform.
  - The PTransform after the read transform is a bit different; it allows one to use Javascript to transform the input strings if, for example, the source format doesn't align well with the BigQuery table format; for documentation on how to use this feature, see this page.
  - The PTransform after the Javascript UDF uses a library function to convert the Json into a tablerow; you can inspect that code here.
  - The write PTransform looks a bit different because instead of making use of a schema that is known at graph compile-time, the code is intended to accept parameters that will only be known at run-time. The NestedValueProvider class is what makes this possible.

Make sure to check out the next lab, which will cover making pipelines that are not simply chains of `PTransform`s, and how you can adapt a pipeline you've built to be a custom Dataflow Template.

End your lab

When you have completed your lab, click **End Lab**. Google Cloud Skills Boost removes the resources you've used and cleans the account for you.

You will be given an opportunity to rate the lab experience. Select the applicable number of stars, type a comment, and then click **Submit**.

The number of stars indicates the following:

- 1 star = Very dissatisfied
- 2 stars = Dissatisfied
- 3 stars = Neutral
- 4 stars = Satisfied
- 5 stars = Very satisfied

You can close the dialog box if you don't want to provide feedback.

For feedback, suggestions, or corrections, please use the **Support** tab.