# BUILDING SERVERLESS DATA PIPELINE IOT TO ANALYTICS



#### Advancements in Internet and

Telecommunications (ICT) accelerated the large –scale deployments of IoT applications including smart city, smart healthcare, and smart factory aiming for faster data processing. The latency and other challenges of cloud-centric IoT, driven edge computing-based data processing architectures. In precise, IoT data analytic requires control for dealing with the complete life cycle of data flow between data sources to sinks by building a set of data pipelines seamlessly deployed on the IoT computing continuum (Edge and clouds).

The execution of data analytic tasks is challenging in the IoT computing continuum due to heterogeneous

hardware architecture at edge and cloud environments. This can be succeeded using Serverless or Function as a service (Faas) cloud computing model, where in tasks are defined as virtual functions and seamlessly migrated and executed within the computing continuum. The serverless data pipelines constitutes a data source, a set of serverless functions that performs specific operations on the data and then ultimately a data sink. Similarly, AWS, Microsoft Azure and Google cloud solutions for IoT data processing that includes the serverless entities as a part of the system. However, cost and latency vary according to cloud provider subscriptions and architecture components.

So, our proposed work outlines the cloud service provider specific IoT services that are composed in designing the serverless data pipelines (SDP) for IoT data processing. Further, we investigate their performance in terms of latency, cost and cold/warm start time of serverless functions for IoT data-oriented pipelines. Aligning to this, we propose AWS and Microsoft Azure based SDP architectures for predictive analytics in Industrial IoT environments and implement the real time predictive Maintenance of Industrial Motor application. Accordingly, we measure the efficiency of AWS and Azure SDP architecture for various performance metrics such as cost, processing time and cold/warm start time for serverless invocations.

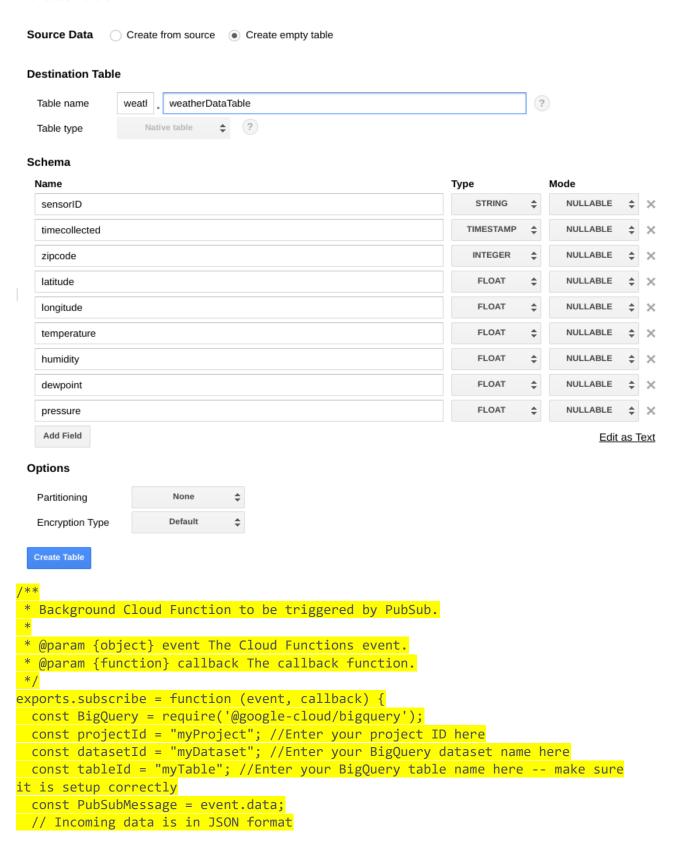
The Raspberry Pi Zero W is recommended for this code lab, but a Raspberry Pi 3 Model B will also work, won't require hammer header pins or a USB hub, has a better CPU, but will cost more. If you choose to move forward with the alternate device, make certain that you have a power supply and an appropriate SD card.

# Create a Big Query table

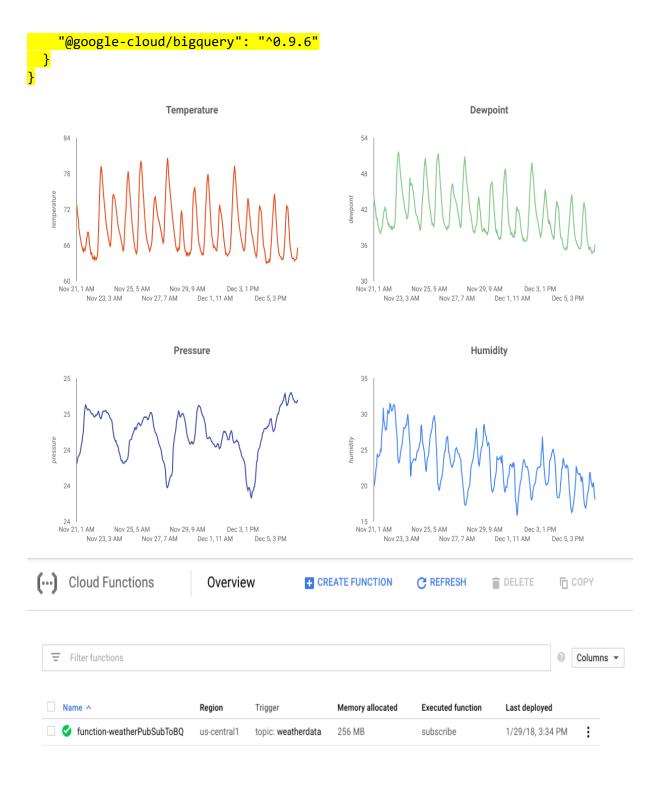
Big Query is a serverless, highly scalable, low-cost enterprise data warehouse and will be an ideal option to store data being streamed from IoT devices while also allowing an analytics dashboard to query the information.

Let's create a table that will hold all the IoT weather data. Select Big Query from the cloud console. This will open Big Query in a new window.

#### **Create Table**



```
const incomingData = PubSubMessage.data ? Buffer.from(PubSubMessage.data,
'base64').toString() : "{'sensorID':'na','timecollected':'1/1/1970
00:00:00','zipcode':'00000','latitude':'0.0','longitude':'0.0','temperature':'-
273', 'humidity': '-1', 'dewpoint': '-273', 'pressure': '0'}";
 const jsonData = JSON.parse(incomingData);
 var rows = [isonData];
console.log(`Uploading data: ${JSON.stringify(rows)}`);
 // Instantiates a client
 const bigguery = BigQuery({
  projectId: projectId
 });
 // Inserts data into a table
 bigquery
   .dataset(datasetId)
  .table(tableId)
  .insert(rows)
    .then((foundErrors) => {
     rows.forEach((row) => console.log('Inserted: ', row));
      if (foundErrors && foundErrors.insertErrors != undefined) {
        foundErrors.forEach((err) => {
            console.log('Error: ', err);
   })
   .catch((err) => {
      console.error('ERROR:', err);
 // [END bigquery_insert_stream]
callback();
In the package. Json tab, paste the following code over the placeholder code that is there
 "name": "function-weatherPubSubToBQ",
 "version": "0.0.1",
 "private": true,
 "license": "Apache-2.0",
 "author": "Google Inc.",
 "dependencies": {
```



Start the data pipeline

Data streaming from a Raspberry Pi

If you constructed a Raspberry Pi IoT weather sensor, start the script that will read the weather data and push it to Google Cloud Pub/Sub. If you aren't in the /home/pi/iot-data-pipeline directory, move there first

cd /home/pi/iot-data-pipeline

Start the weather script

python checkWeather.py

# Check that data is flowing

gcloud beta functions logs read function-weatherPubSubToBQ

The logs should show that the function is executing, data is being received and that it is being inserted into Big Query

```
function-weatherPubSubToRQ 28796420510154 2018-01-30 20:01:18.750 Function execution started function-weatherPubSubToRQ 28796420510154 2018-01-30 20:01:19.878 Incoming data: (object Object) function-weatherPubSubToRQ 28796420510154 2018-01-30 20:01:19.923 Function execution took 1174 ms, finished with status: 'ok' function-weatherPubSubToRQ 28796420510154 2018-01-30 20:01:24.351 Inserted: function-weatherPubSubToRQ 28796420510154 2018-01-30 20:01:25.051 (pressure: '24.19', temperature: '70.90', dewpoint: '41.59', timecollected: '2018-01-30 20:01:25.051 latitude: '37.421655', sensorID: 's-testing', zigood: '37.421655', sensorID: 's-testing', zigood: '-122.085637', humidity: '18.58' !
```

#### Create a data studio dashboard

Confirm by clicking the add a data report button

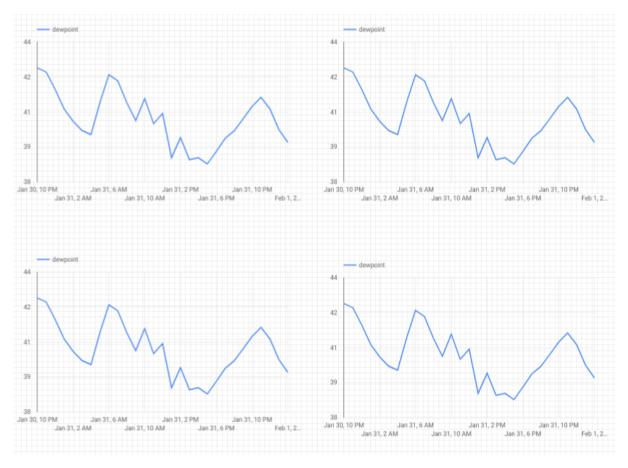
#### You are about to add a data source to this report



Note that **Report Editors** can create charts using the new data source(s), and can add dimensions and metrics not currently included in the report.



Click the graph on the sheet and copy/paste (Ctrl-C/Ctrl-V) it 3 times. Align the graphs so that each has ¼ of the layout.



### Conclusion

We've created an entire data pipeline! In doing so, we've learned how to use Google Pub/Sub, how to deploy a serverless Function, how to leverage Big Query and how to create an analytics dashboard using Data Studio. In addition, we've seen how the Google Cloud SDK can be used securely to bring data into the Google Cloud Platform. Finally, we now have some hands-on experience with an important architectural pattern that can handle high volumes while maintaining availability.