ETL Process using AWS

Objective:

- To leverage ETL tools available in the Amazon cloud with help of employee migration data.
- To evaluate and compare Glue and EMR (ETL AWS Technologies) costs and computational effort.

TechStack:

- 1. AWS Glue Studio, Cloud 9 Console.
- 2. AWS EMR EC2
- 3. S3
- 4. PySpark
- 5. Git

Business Scenario:

Motivation behind choosing this use case is, in scenarios when the company becomes a subsidiary of a parent company, employee data needs to be migrated.

For Example: MLReply has become an independent company from Data Reply since August. Leveraging ETL process in the cloud environment for such cases when the job runs daily, two factors need to be monitored:

- What would be the costs at daily rate.
- How much development time does it take.

Data Description:

The employee migration data contains 2 tables. The main data table contains the information of employees with 9 columns and one million records. The second data table contains the information of employee names that has been changed in cases where some employees have new names.

Following are the fields in main table:

Employee ID, Name, Gender, Address, Country, Email, Unit, Experience, Domain.

Implementation:

AWS GLUE:

- Serverless data integration service
- Easy to discover, prepare and combine data for analytics, ML, and App Development.

Steps:

- 1. Creating Cloud9 environment to get the files from Git.
- 2. Create S3 bucket inside cloud 9 IDE.
- **3.** Create Glue Data Catalog For a given data set, you can store its table definition, physical location, add business relevant attributes, as well as track how this data has changed over time.
- 4. Add database and crawlers to crawl the CSV and JSON folders.
- 5. Run the crawlers The table schema will be automatically generated by the crawler based on the csv file (in this use-case).

- **6.** Creating AWS environment i.e Glue Dev Endpoint to iteratively develop and test the extract, transform, and load (ETL) scripts
- **7.** Connect development notebooks like Sagemaker Notebooks to the Dev Endpoint to test the code snippets.
- 8. Deploy and Run the ETL Job.

Observations:

- Amazon Glue's pay-as-you-go rate of \$0.44 per DPU (One DPU=4 vCPU and 16 GB of memory)
- It might seem reasonable at first, organizations commonly find themselves with bloated bills after prolonged use.
- The cost depends on the jobs run and dev-endpoint. In this scenario, before even deploying the jobs the cost was more for dev-endpoint.
- Below is the tabulation of the costs:

Time	Cost
per DPU-Hour	0.44\$
1h	21\$
4 DAYS	100\$

Merits:

- 1. AWS Glue is capable of automatically generating ETL pipeline code in Scala or Python
- 2. Serverless architecture and job scheduling.
- 3. Increased data visibility By acting as the metadata repository for information on your data sources and stores
- 4. Developer endpoints For users who prefer to manually create and test their own custom ETL scripts

Demerits:

- 1. Only two languages When it comes to customizing ETL codes, AWS Glue only supports Python and Scala
- 2. Limited integrations
- 3. Expensive when jobs has to run on daily basis.

Amazon Elastic MapReduce (EMR):

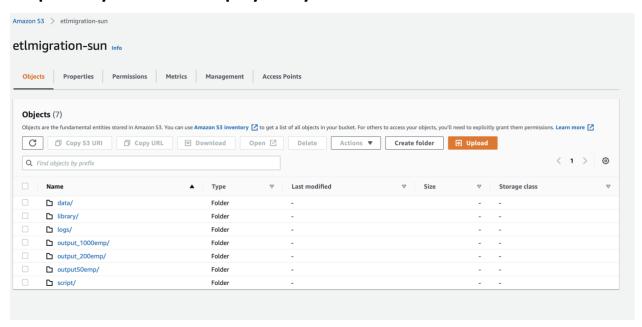
- 1. EMR is a big data platform designed to reduce the cost of processing and analyzing huge amounts of data.
- 2. A managed service where you configure your own cluster of EC2 instances.

Steps:

- 1. Creating cluster using advanced options
- 2. Specify the software configuration and add step according to the application. In this case, it is Spark Application.
- 3. Choose the hardware, instance type for master and cluster node. Add the EBS root volume.
- 4. Add tags and general options according to the use case.
- 5. Check for EC2 security groups and generate EC2 Key pair.
- 6. Once the cluster moves from waiting to Ready state, log in to the EMR Cluster.

Snapshot1: Login to EMR Cluster

Snapshot2: Files stored in S3 bucket. Use the location of S3 for the script that you want to deploy it in your cluster.



Snapshot3: Copied files from AWS S3 to my EMR cluster.

```
[[ec2-user@ip-172-31-2-36 emr]$ 1s -lrt
total 28
-rw-rw-r-- 1 ec2-user ec2-user 2713 Sep 7 16:45 ETL2.py
-rw-rw-r-- 1 ec2-user ec2-user 2165 Sep 9 17:12 ETL.py
-rw-rw-r-- 1 ec2-user ec2-user 2764 Sep 13 14:05 data-migration.py
-rw-rw-r-- 1 ec2-user ec2-user 2765 Sep 13 14:49 data-migration_1000emp.py
-rw-rw-r-- 1 ec2-user ec2-user 2757 Sep 15 16:30 ETL_50emp.py
-rw-rw-r-- 1 ec2-user ec2-user 2762 Sep 15 16:43 ETL_200.py
-rw-rw-r-- 1 ec2-user ec2-user 2756 Sep 15 16:54 ETL_1000emp.py
[ec2-user@ip-172-31-2-36 emr]$ ■
```

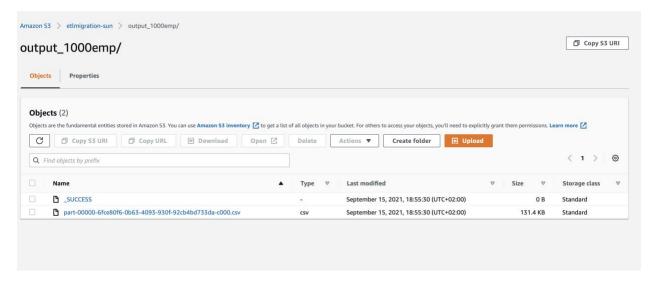
Snapshot4: Spark-Submit the python script using the spark application to run the application.

```
The content of the co
```

NOTE:

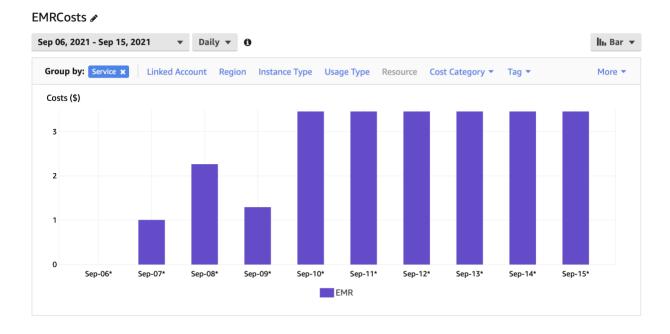
- Spark submit can only be done as a root user.
- If the application fails, or it has some errors, it will be displayed in the CLI or can even check log files.

Snapshot5: Output files generated and stored in S3 AWS.



Observations:

- Billing and Cost Management is one of the important perspectives that one should also take care of in cloud when working on any use-case.
- Following is the chart on the cost usage under the cost explorer:



Service	EMR(\$)	Total cost (\$)
Service Total	39.274266672	39.274266672
2021-09-07	1.008	1.008
2021-09-08	2.266266672	2.266266672
2021-09-09	1.296	1.296
2021-09-10	3.456	3.456
2021-09-11	3.456	3.456
2021-09-12	3.456	3.456
2021-09-13	3.456	3.456
2021-09-14	3.456	3.456
2021-09-15	3.456	3.456
2021-09-16	3.456	3.456
2021-09-17	3.456	3.456
2021-09-18	3.456	3.456
2021-09-19	3.456	3.456
2021-09-20	144	144

Benchmarking was done regarding the development time:

EMR-Spark	Script Execution Time	EMR Cost	Cluster up and Run time
50 rows	2 seconds	5.72\$	119.214 hrs
200 rows	5 seconds	14.94\$	311.214 hrs
1000 rows	10 seconds	\$23.29	485.214 Hrs

Merits:

- 1. As a cloud based computing service, Amazon EMR offers a data solution without the cost of maintaining an in-house computing infrastructure server.
- 2. Saves time in tasks like system administration.
- 3. In comparison with Glue, it saves a lot of costs for the company.

Demerits:

- 1. Synchronization of metadata from S3 tends to become inconsistent sometimes.
- 2. Management overhead would not be as simple as Glue.

Alternate/Similar technologies:

- 1. Amazon Apache Airflow for scheduling ETL jobs.
- 2. AWS Data Pipeline
- 3. AWS Batch

Future Scope:

- Orchestrate Apache Spark applications using AWS Step functions and Apache Livy(REST API's).
- Emr Apache Livy Sagemaker.