World Bank Global Health - Data Analysis and Visualization

USING GOOGLE CLOUD PLATFORM (GCP)

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1 Project Goal

The project is to explore the World Bank Global Health dataset available from Google Dataset https://console.cloud.google.com/marketplace/product/the-world-bank/global-health.

This project was a part of the **Grace Hoppers TechPathways - Data Engineering Program**.

As part of the project, we were asked to create a CI/CD pipeline based on the architecture given in **Figure 1** to read data from dataset and build visualizations on it.

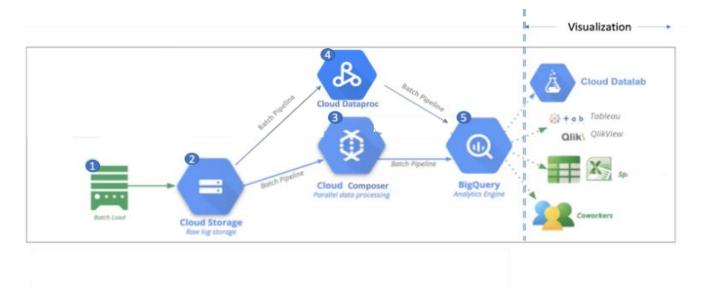


Figure 1: Architecture of the CI/CD Pipeline

The following points must be considered while developing this pipeline:

- 1. It must be optimized to be able to handle cost and scaling
- 2. The following insights had to be produced on the clean dataset using Datalab or other tools:
 - a) What is the average age of males and females in different countries around the world
 - b) Correlation between Health Expenditure and survival ages in the two genders around the world
 - c) Correlation between School enrollment and unemployment for males and females around the world
 - d) Average age of first pregnancy around the world

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e) Analysis of age of marriage and infant mortality rate across different demograpics

2 Understanding the Architecture

As per the architecture explained in the above Figure 1, the following objectives must be met:

- We have to load the WorldBank dataset in BigQuery using a CI/CD pipeline.
- The Pipeline must contain the Google Composer and Dataproc Cluster.
- Files which are not dependent on each other must be read parallelly and loaded to Bigquery.
- The data loaded in bigguery must be cleaned, transformed and easy to analyze.
- Bigguery optimization using Clustering and Partitioning must be done.

3 Implementation

The implementation was broken down into the following tasks. Every task was implemented using Google Cloud Technologies:

- Downloading Data from the Google Dataset as CSV Files to Google Storage Bucket
- Understanding the Data
- Creating Google Composer
- Creating a CI/CD Pipeline using Cloud Build
- Visualizing Data using DataLab

3.1 Downloading Data

As the very first step, data is downloaded from the Google Dataset to a Google Storage Bucket. It consists of the following csv files

- 1. Wh country series definition.csv
- 2. Wh country summary.csv
- 3. Wh_health_nutrition_population.csv
- 4. Wh series summary.csv
- 5. Wh series times.csv

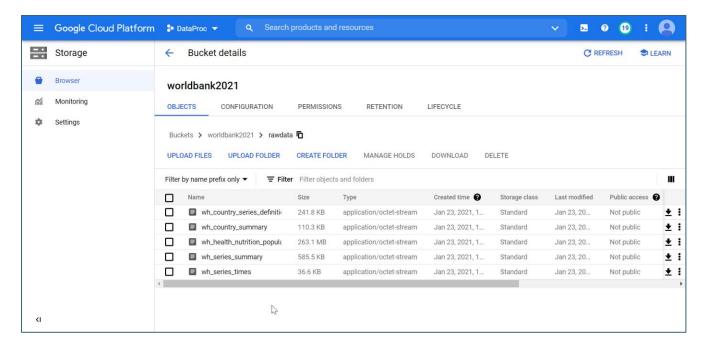


Figure 2: Google Storage Bucket

3.2 Understanding the Data

The World Bank data consists of demographic and other statistical data related to Population, Employment, Health, GDP, Energy Consumption, etc. for all the countries from the year 1960 to 2018.

From the five files downloaded in section 3.1, the *health_nutrition_population.csv* file would be used for all the data exploration tasks as that contains all the values for the various indicators. The rest of the files was used to understand the indicators for various countries.

3.3 Creating the CI/CD Pipeline

The CI/CD Pipeline is created using the Google Cloud Composer and Cloud Build. A composer is created as shown in Figure below:

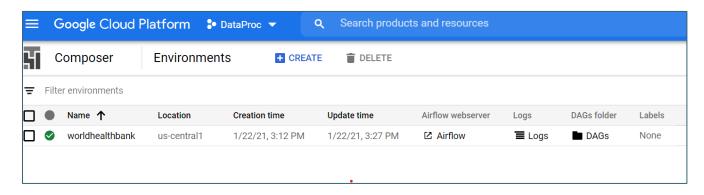


Figure 3: Google Composer

The Cloud Build trigger is created as shown below. This trigger is integrated with my Github repository https://github.com/Sadiya-Dalvi/GoogleComposer. Whenever a new dag file is checkedin to the Master branch a Cloud Build job is triggered to sync the Airflow Cloud Storage bucket. Once the dag is detected by the composer and the airflow, the pipeline gets triggered.

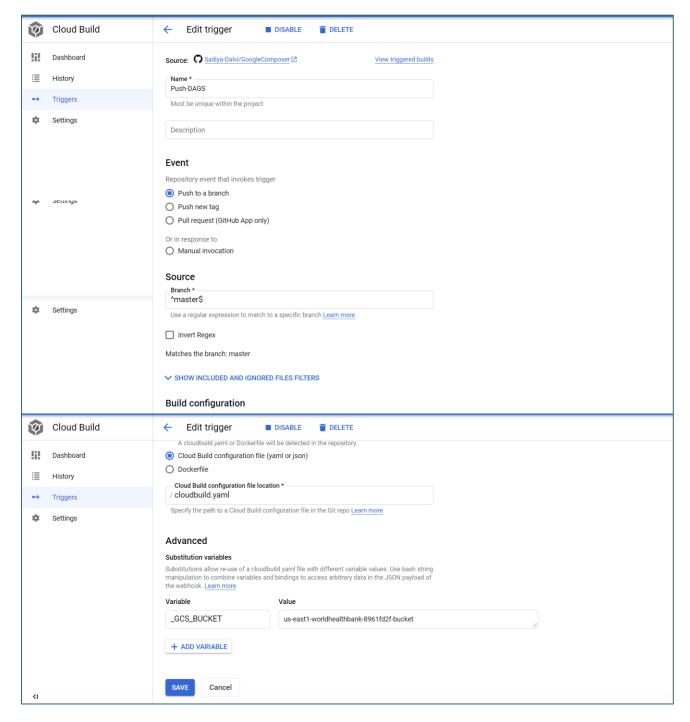


Figure 4: CloudBuild

3.3.1 Cloudbuild.yaml

```
steps:
         - name: ubuntu
           args: ['bash', '-c', "echo '$COMMIT_SHA' > REVISION.txt"]
         - name: gcr.io/cloud-builders/gsutil
           args:
             - '-m'
             - 'rsync'
             - '-d'
             - '-r'
             - 'dags'
             - 'gs://${_GCS_BUCKET}/dags'
         - name: gcr.io/cloud-builders/gsutil
           args:
             - '-m'
             - 'rsync'
             - '-d'
             - '-r'
             - 'plugins'
             - 'gs://${_GCS_BUCKET}/plugins'
```

3.3.2 Composer DAG 'load_gh_project_dag.py'

Created the following pipeline using google composer and apache airflow where the tasks are given below. The DAG code is as below:

```
from __future__ import print_function
import datetime

from airflow import models
from airflow.operators import bash_operator
from airflow.operators import python_operator
from airflow.contrib.operators import dataproc_operator
from airflow.utils import trigger_rule
from airflow.utils.dates import days_ago

yesterday = datetime.datetime.combine(
    datetime.datetime.today() - datetime.timedelta(1),
    datetime.datetime.min.time())

data_set = "worldbankhealth23012021"

default_dag_args = {
    # Setting start date as yesterday starts the DAG immediately when it is
```

```
def greeting():
create dataproc cluster = dataproc operator.DataprocClusterCreateOperator(
dataproc pyspark 1 = dataproc operator.DataProcPySparkOperator(
dataproc pyspark 2 = dataproc operator.DataProcPySparkOperator(
```

```
dataproc pyspark 4 = dataproc operator.DataProcPySparkOperator(
dataproc pyspark 5 = dataproc operator.DataProcPySparkOperator(
delete dataproc cluster = dataproc operator.DataprocClusterDeleteOperator(
   trigger_rule = trigger rule.TriggerRule.ALL DONE
create dataproc cluster >> dataproc pyspark 1 >> delete dataproc cluster
create_dataproc_cluster >> dataproc_pyspark_3 >> delete_dataproc_cluster
```

3.3.3 Dataproc_load_bq.py

```
#test
#import pyspark
import sys
from pyspark.sql import SparkSession
from pyspark.sql.types import TimestampType, StringType
import pyspark.sql.functions as F
#from google.cloud import bigquery

#import datetime
#gs://worldbank2021/rawdata/wh_country_series_definition
#gs://worldbank2021/rawdata/wh_country_summary
#gs://worldbank2021/rawdata/wh health nutrition population
```

```
spark = SparkSession.builder.appName('World Health Data').getOrCreate()
file_path = "gs://worldbank2021/rawdata/" + table_name
df = spark.read.csv(file path, header=True, inferSchema=True)
df = df.dropDuplicates()
bucket = "worldbank2021"
    df = df.dropna(subset=['series code'])
```

```
F.to date(F.col('year').cast(StringType()),'yyyy'))
```

3.3.4 Task Descriptions

1. Task id(create_dataproc_cluster) - Created a dataproc cluster

Logs from Apache Airflow are given below:

```
[2021-01-23 07:04:42,699] {taskinstance.py:882} INFO - Starting attempt 1 of 1 [2021-01-23 07:04:42,700] {taskinstance.py:883} INFO - [2021-01-23 07:04:42,754] {taskinstance.py:902} INFO - Executing <Task(DataprocClusterCreateOperator): create_dataproc_cluster> on 2021-01-22T00:00:00+00:00 [2021-01-23 07:04:42,760] {standard_task_runner.py:54} INFO - Started process 9759 to run task [2021-01-23 07:04:42,868] {standard_task_runner.py:77} INFO - Running: ['airflow', 'run', 'Project_WH_Parallel_Datapipeline', 'create_dataproc_cluster', '2021-01-22T00:00:00+00:00', '--job_id', '285', '--pool', 'default_pool', '--raw', '-sd', 'DAGS_FOLDER/load_gh_project_dag.py', '--cfg_path', '/tmp/tmp90u771sg']
```

```
[2021-01-23 07:04:42,870] {standard task runner.py:78} INFO - Job 285: Subtask
create dataproc cluster
[2021-01-23 07:04:43,618] {logging mixin.py:112} INFO - Running <TaskInstance:
Project WH Parallel Datapipeline.create dataproc cluster 2021-01-22T00:00:00+00:00
[running] > on host airflow-worker-84bdd7d564-7m64g
[2021-01-23 07:04:43,967] {dataproc operator.py:447} INFO - Creating cluster:
cluster-58-wb@-@{"workflow": "Project_WH_Parallel_Datapipeline", "task-id":
"create_dataproc_cluster", "execution-date": "2021-01-22T00:00:00+00:00"}
[2021-01-23 07:04:43,977] {gcp api_base_hook.py:145} INFO - Getting connection using
`google.auth.default()` since no key file is defined for hook.@-@{"workflow":
"Project_WH_Parallel_Datapipeline", "task-id": "create_dataproc_cluster", "execution-
date": "2021-01-22T00:00:00+00:00"}
[2021-01-23 07:04:45,915] {gcp api base hook.py:145} INFO - Getting connection using
 google.auth.default() ` since no key file is defined for hook.@-@{"workflow":
"Project WH Parallel Datapipeline", "task-id": "create dataproc cluster", "execution-
date": "2021-01-22T00:00:00+00:00"}
[2021-01-23 07:04:46,151] {gcp_dataproc_hook.py:250} INFO - Waiting for Dataproc
Operation projects/dataproc-300110/regions/us-east1/operations/7e9f1383-54db-31c6-
9ab6-6fedec239487 to finish@-@{"workflow": "Project WH Parallel Datapipeline", "task-
id": "create dataproc cluster", "execution-date": "2021-01-22T00:00:00+00:00"}
[2021-01-23 07:06:56,766] {gcp dataproc hook.py:275} INFO - Dataproc Operation
projects/dataproc-300110/regions/us-east1/operations/7e9f1383-54db-31c6-9ab6-
6fedec239487 done@-@{"workflow": "Project WH Parallel Datapipeline", "task-id":
"create_dataproc_cluster", "execution-date": "2021-01-22T00:00:00+00:00"}
[2021-0\overline{1}-23\ 07:0\overline{6}:56,907] {taskinstance.py:1071} INFO - Marking task as
{\tt SUCCESS.dag\_id=Project\_WH\_Parallel\_Datapipeline,\ task\_id=create\_dataproc\_cluster,}
execution date=20210122T000000, start date=20210123T070442, end date=20210123T070656
[2021-01-23 07:06:58,074] {local task job.py:102} INFO - Task exited with return code
```

2. **Task id(dataproc_pyspark_1)** – Ran 'Load_BQ_spark_job_1' job. This job executes the dataproc_load_bq.py script to read data from **wh_country_series_definition.csv** file, extract and cleaning it to drop duplicates, dropping null values and writes it to bigquery table.

Log Output from the Dataproc Cluster job is given below:

```
21/01/23 07:17:17 WARN org.apache.spark.scheduler.cluster.YarnScheduler: Initial job
has not accepted any resources; check your cluster UI to ensure that workers are
registered and have sufficient resources
|-- country code: string (nullable = true)
|-- series code: string (nullable = true)
|-- description: string (nullable = true)
There are 3368 rows in the Dataframe after dropping duplicates.
21/01/23 07:17:38 INFO com.google.cloud.spark.bigquery.BigQueryUtilScala: BigQuery
client project id is [dataproc-300110], derived from the parentProject option
21/01/23 07:22:12 INFO com.google.cloud.spark.bigquery.BigQueryWriteHelper:
Submitted load to GenericData{classInfo=[datasetId, projectId, tableId],
{datasetId=worldbankhealth23012021, projectId=dataproc-300110,
tableId=wh_country_series_definition}}. jobId: JobId{project=dataproc-300110,
job=b0e23981-04ab-4242-9429-d6dc58cee6d0, location=US}
21/01/23 07:22:19 INFO com.google.cloud.spark.bigquery.BigQueryWriteHelper: Done
loading to dataproc-300110.worldbankhealth23012021.wh country series definition.
jobId: JobId(project=dataproc-300110, job=b0e23981-04ab-4242-9429-d6dc58cee6d0,
location=US}
21/01/23 07:22:20 INFO org.spark_project.jetty.server.AbstractConnector: Stopped
Spark@70e6cecb{HTTP/1.1, [http/1.1]}{0.0.0.0:4043}
Job output is complete
```

3. **Task id(dataproc_pyspark_2)** – Ran 'Load_BQ_spark_job_2' job. This job executes the dataproc_load_bq.py script to read data from **wh_country_summary.csv** file, extract and cleaning it to drop duplicates, dropping null values and writes it to bigguery table.

Log Output from the Dataproc Cluster job is given below:

```
21/01/23 07:13:03 WARN org.apache.spark.scheduler.cluster.YarnScheduler: Initial job
has not accepted any resources; check your cluster UI to ensure that workers are
registered and have sufficient resources
 |-- country code: string (nullable = true)
 |-- short name: string (nullable = true)
 |-- table name: string (nullable = true)
 |-- long_name: string (nullable = true)
 |-- two_alpha_code: string (nullable = true)
 |-- currency_unit: string (nullable = true)
 |-- special_notes: string (nullable = true)
 |-- region: string (nullable = true)
 |-- income group: string (nullable = true)
 |-- wb 2 code: string (nullable = true)
 |-- national_accounts_base_year: string (nullable = true)
 |-- national_accounts_reference_year: integer (nullable = true)
 |-- sna price_valuation: string (nullable = true)
 |-- lending category: string (nullable = true)
 |-- other groups: string (nullable = true)
 |-- system_of_national_accounts: string (nullable = true)
 |-- alternative conversion factor: string (nullable = true)
 |-- ppp_survey_year: string (nullable = true)
 |-- balance_of_payments_manual_in_use: string (nullable = true)
 |-- external_debt_reporting_status: string (nullable = true)
 |-- system_of_trade: string (nullable = true)
 |-- government accounting concept: string (nullable = true)
 |-- imf data dissemination standard: string (nullable = true)
 |-- latest population census: string (nullable = true)
 |-- latest household survey: string (nullable = true)
 |-- source_of_most_recent_income_and_expenditure_data: string (nullable = true)
 |-- vital registration complete: string (nullable = true)
 |-- latest agricultural census: string (nullable = true)
 |-- latest industrial data: integer (nullable = true)
 |-- latest trade data: integer (nullable = true)
 |-- latest_water_withdrawal_data: string (nullable = true)
21/01/23 07:13:21 WARN org.apache.spark.util.Utils: Truncated the string
representation of a plan since it was too large. This behavior can be adjusted by
setting 'spark.debug.maxToStringFields' in SparkEnv.conf.
There are 262 rows in the Dataframe after dropping duplicates.
There are 262 rows in the Dataframe after dropping nulls.
21/01/23 07:13:33 INFO com.google.cloud.spark.bigquery.BigQueryUtilScala: BigQuery
client project id is [dataproc-300110], derived from the parentProject option
21/01/23 07:17:09 INFO com.google.cloud.spark.bigquery.BigQueryWriteHelper:
Submitted load to GenericData{classInfo=[datasetId, projectId, tableId],
{datasetId=worldbankhealth23012021, projectId=dataproc-300110,
tableId=wh country summary}}. jobId: JobId{project=dataproc-300110, job=609d36f4-
f90a-49e9-ab2e-9833c0cfb0e9, location=US}
21/01/23 07:17:20 INFO com.google.cloud.spark.bigquery.BigQueryWriteHelper: Done
loading to dataproc-300110.worldbankhealth23012021.wh country summary. jobId:
JobId{project=dataproc-300110, job=609d36f4-f90a-49e9-ab2e-9833c0cfb0e9,
location=US}
21/01/23 07:17:20 INFO org.spark project.jetty.server.AbstractConnector: Stopped
Spark@6cf95103{HTTP/1.1,[http/1.1]}{0.0.0.0:4041}
Job output is complete
```

4. **Task id(dataproc_pyspark_3)** – Ran 'Load_BQ_spark_job_3' job. This job executes the dataproc_load_bq.py script to read data from **wh_health_nutrition_population.csv** file, extract and cleaning it to drop duplicates, dropping null values and writes it to bigguery table.

Additionally since this is the table which we would use for our visualizations, an additional column, dateYear is added to this. This is done to partition the bigquery table on this column since there was no date column available in the original table. Partitioning helps with query optimizations. Further we also use the cluster property on indicator_code column for performance improvement.

Log Output from the Dataproc Cluster job is given below:

```
21/01/23 07:08:06 INFO org.spark project.jetty.util.log: Logging initialized
21/01/23 07:08:07 INFO org.spark project.jetty.server.Server: jetty-9.3.z-SNAPSHOT,
build timestamp: unknown, git hash: unknown
21/01/23 07:08:07 INFO org.spark_project.jetty.server.Server: Started @18821ms
21/01/23 07:08:07 WARN org.apache.spark.util.Utils: Service 'SparkUI' could not
bind on port 4040. Attempting port 4041.
21/01/23 07:08:07 WARN org.apache.spark.util.Utils: Service 'SparkUI' could not
bind on port 4041. Attempting port 4042.
21/01/23 07:08:07 WARN org.apache.spark.util.Utils: Service 'SparkUI' could not
bind on port 4042. Attempting port 4043.
21/01/23 07:08:07 WARN org.apache.spark.util.Utils: Service 'SparkUI' could not
bind on port 4043. Attempting port 4044.
21/01/23 07:08:07 INFO org.spark project.jetty.server.AbstractConnector: Started
ServerConnector@2449bef3{HTTP/1.\overline{1},[http/1.1]}{0.0.0.0:4044}
21/01/23 07:08:08 WARN org.apache.spark.scheduler.FairSchedulableBuilder: Fair
Scheduler configuration file not found so jobs will be scheduled in FIFO order. To
use fair scheduling, configure pools in fairscheduler.xml or set
spark.scheduler.allocation.file to a file that contains the configuration.
21/01/23 07:08:12 INFO org.apache.hadoop.yarn.client.RMProxy: Connecting to
ResourceManager at cluster-58-wb-m/10.142.15.199:8032
21/01/23 07:08:13 INFO org.apache.hadoop.yarn.client.AHSProxy: Connecting to
Application History server at cluster-58-wb-m/10.142.15.199:10200
21/01/23 07:08:22 INFO org.apache.hadoop.yarn.client.api.impl.YarnClientImpl:
Submitted application application 1611385532354 0005
File name is qs://worldbank2021/rawdata/wh health nutrition population
21/01/23 07:17:51 WARN org.apache.spark.scheduler.cluster.YarnScheduler: Initial
job has not accepted any resources; check your cluster UI to ensure that workers
are registered and have sufficient resources
root
|-- country name: string (nullable = true)
 |-- country code: string (nullable = true)
 |-- indicator name: string (nullable = true)
 |-- indicator code: string (nullable = true)
 |-- value: double (nullable = true)
 |-- year: integer (nullable = true)
There are 3019732 rows in the Dataframe after dropping duplicates.
There are 3019732 rows in the Dataframe after dropping nulls.
21/01/23 07:18:56 INFO com.google.cloud.spark.bigquery.BigQueryUtilScala: BigQuery
client project id is [dataproc-300110], derived from the parentProject option
21/01/23 07:23:09 INFO com.google.cloud.spark.bigquery.BigQueryWriteHelper:
Submitted load to GenericData{classInfo=[datasetId, projectId, tableId],
{datasetId=worldbankhealth23012021, projectId=dataproc-300110,
tableId=wh_health_nutrition_population}}.jobId: JobId{project=dataproc-300110,
job=25a700b8-94c5-4052-b9af-a0a3e5da9629, location=US}
21/01/23 07:23:18 INFO com.google.cloud.spark.bigquery.BigQueryWriteHelper: Done
loading to dataproc-300110.worldbankhealth23012021.wh health nutrition population.
jobId: JobId{project=dataproc-300110, job=25a700b8-94c5-4052-b9af-a0a3e5da9629,
location=US}
21/01/23 07:23:19 INFO org.spark project.jetty.server.AbstractConnector: Stopped
Spark@2449bef3{HTTP/1.1,[http/1.1]}{0.0.0.0:4044}
Job output is complete
```

5. **Task id(dataproc_pyspark_4)** – Ran 'Load_BQ_spark_job_4' job. This job executes the dataproc_load_bq.py script to read data from **wh_series_summary.csv** file, extract and cleaning it to drop duplicates, dropping null values and writes it to bigguery table.

```
21/01/23 07:07:30 INFO org.spark project.jetty.util.log: Logging initialized @3567ms
21/01/23 07:07:30 INFO org.spark project.jetty.server.Server: jetty-9.3.z-SNAPSHOT,
build timestamp: unknown, git hash: unknown
21/01/23 07:07:30 INFO org.spark project.jetty.server.Server: Started @3669ms
21/01/23 07:07:30 INFO org.spark project.jetty.server.AbstractConnector: Started
ServerConnector@3f07e249{HTTP/1.1,[http/1.1]}{0.0.0.0:4040}
21/01/23 07:07:30 WARN org.apache.spark.scheduler.FairSchedulableBuilder: Fair
Scheduler configuration file not found so jobs will be scheduled in FIFO order. To
use fair scheduling, configure pools in fairscheduler.xml or set
spark.scheduler.allocation.file to a file that contains the configuration.
21/01/23 07:07:31 INFO org.apache.hadoop.yarn.client.RMProxy: Connecting to
ResourceManager at cluster-58-wb-m/10.142.15.199:8032
21/01/23 07:07:32 INFO org.apache.hadoop.yarn.client.AHSProxy: Connecting to
Application History server at cluster-58-wb-m/10.142.15.199:10200
21/01/23 07:07:37 INFO org.apache.hadoop.yarn.client.api.impl.YarnClientImpl:
Submitted application application 1611385532354 0001
File name is gs://worldbank2021/rawdata/wh series summary
 |-- series code: string (nullable = true)
 |-- topic: string (nullable = true)
 |-- indicator name: string (nullable = true)
 |-- short_definition: string (nullable = true)
 |-- long_definition: string (nullable = true)
 |-- unit of measure: string (nullable = true)
 |-- periodicity: string (nullable = true)
 |-- base period: string (nullable = true)
 |-- other notes: string (nullable = true)
 |-- aggregation method: string (nullable = true)
 |-- limitations and exceptions: string (nullable = true)
 |-- notes_from_original_source: string (nullable = true)
 |-- general comments: string (nullable = true)
 |-- source: string (nullable = true)
 |-- statistical concept and methodology: string (nullable = true)
 |-- development relevance: string (nullable = true)
 |-- related_source_links: string (nullable = true)
 |-- other web links: string (nullable = true)
 |-- related_indicators: string (nullable = true)
 |-- license type: string (nullable = true)
There are 542 rows in the Dataframe after dropping duplicates.
There are 542 rows in the Dataframe after dropping nulls.
21/01/23 07:08:35 INFO com.google.cloud.spark.bigquery.BigQueryUtilScala: BigQuery
client project id is [dataproc-300110], derived from the parentProject option
21/01/23 07:12:55 INFO com.google.cloud.spark.bigquery.BigQueryWriteHelper:
Submitted load to GenericData{classInfo=[datasetId, projectId, tableId],
{datasetId=worldbankhealth23012021, projectId=dataproc-300110,
tableId=wh_series_summary}}. jobId: JobId{project=dataproc-300110, job=0056f5f3-
555e-410c-8949-0c86271d9df4, location=US}
21/01/23 07:13:11 INFO com.google.cloud.spark.bigquery.BigQueryWriteHelper: Done
loading to dataproc-300110.worldbankhealth23012021.wh series summary. jobId:
JobId{project=dataproc-300110, job=0056f5f3-555e-410c-8949-0c86271d9df4,
location=US}
21/01/23 07:13:11 INFO org.spark project.jetty.server.AbstractConnector: Stopped
Spark@3f07e249{HTTP/1.1,[http/1.1]}{0.0.0.0:4040}
Job output is complete
```

6. **Task id(dataproc_pyspark_5)** – Ran 'Load_BQ_spark_job_5' job. This job executes the dataproc_load_bq.py script to read data from **wh_series_times.csv** file, extract and cleaning it to drop duplicates, dropping null values and writes it to bigquery table.

```
21/01/23 07:13:16 WARN org.apache.spark.scheduler.cluster.YarnScheduler: Initial job
has not accepted any resources; check your cluster UI to ensure that workers are
registered and have sufficient resources
 |-- series code: string (nullable = true)
 |-- year: integer (nullable = true)
 |-- description: string (nullable = true)
There are 420 rows in the Dataframe after dropping duplicates.
There are 420 rows in the Dataframe after dropping nulls.
21/01/23 07:13:37 INFO com.google.cloud.spark.bigquery.BigQueryUtilScala: BigQuery
client project id is [dataproc-300110], derived from the parentProject option
21/01/23 07:17:33 INFO com.google.cloud.spark.bigquery.BigQueryWriteHelper:
Submitted load to GenericData{classInfo=[datasetId, projectId, tableId],
{datasetId=worldbankhealth23012021, projectId=dataproc-300110,
tableId=wh series times}}. jobId: JobId{project=dataproc-300110, job=1d4dd7c9-3694-
4b05-b3f2-590b5c2aad0c, location=US}
21/01/23 07:17:46 INFO com.google.cloud.spark.bigquery.BigQueryWriteHelper: Done
loading to dataproc-300110.worldbankhealth23012021.wh series times. jobId:
JobId{project=dataproc-300110, job=1d4dd7c9-3694-4b05-b3f2-590b5c2aad0c,
location=US}
21/01/23 07:17:46 INFO org.spark_project.jetty.server.AbstractConnector: Stopped
Spark@77f31878{HTTP/1.1,[http/1.1]}{0.0.0.0:4042}
Job output is complete
```

7. **Task id (delete_dataproc_cluster)** - Deleted the dataproc cluster 'delete_dataproc_cluster' after the tables were loaded in Bigguery

```
[2021-01-23 07:23:32,624] {taskinstance.py:882} INFO - Starting attempt 1 of 1
[2021-01-23 07:23:32,624] {taskinstance.py:883} INFO -
[2021-01-23 07:23:32,695] {taskinstance.py:902} INFO - Executing <Task(DataprocClusterDe
leteOperator): delete dataproc cluster> on 2021-01-22T00:00:00+00:00
[2021-01-23 07:23:32,728] {standard task runner.py:54} INFO - Started process 9753 to ru
n task
[2021-01-23 07:23:33,283] {standard task runner.py:77} INFO - Running: ['airflow', 'run'
, 'Project WH Parallel Datapipeline, 'delete dataproc cluster, '2021-01-22T00:00:00+00
:00', '--job_id', '295', '--pool', 'default_pool', '--raw', '-sd', 'DAGS_FOLDER/load_gh_
project dag.py', '--cfg path', '/tmp/tmpyl03n3wb']
[2021-01-23 07:23:33,286] {standard task runner.py:78} INFO - Job 295: Subtask delete da
taproc cluster
[2021-01-23 07:23:34,232] {logging mixin.py:112} INFO - Running <TaskInstance: Project W
H Parallel Datapipeline.delete dataproc cluster 2021-01-22T00:00:00+00:00 [running]> on
host airflow-worker-84bdd7d564-wjwcl
[2021-01-23 07:23:34,403] {dataproc operator.py:620} INFO - Deleting cluster: cluster-58
-wb in us-east10-0{"workflow": "Project WH Parallel Datapipeline", "task-id": "delete da
taproc cluster", "execution-date": "2021-01-22T00:00:00+00:00"}
```

```
[2021-01-23 07:23:34,404] {gcp api base hook.py:145} INFO - Getting connection using `go
ogle.auth.default()` since no key file is defined for hook.@-@{"workflow": "Project WH P
arallel Datapipeline", "task-id": "delete dataproc cluster", "execution-date": "2021-01-
22T00:00:00+00:00"}
[2021-01-23 07:23:34,988] {gcp api base hook.py:145} INFO - Getting connection using `go
ogle.auth.default()` since no key file is defined for hook.@-@{"workflow": "Project_WH_P
arallel Datapipeline", "task-id": "delete dataproc cluster", "execution-date": "2021-01-
22T00:00:00+00:00"}
[2021-01-23 07:23:35,359] {gcp dataproc hook.py:250} INFO - Waiting for Dataproc Operati
on projects/dataproc-300110/regions/us-east1/operations/1bd8742b-14a7-34dd-b139-675c21a3
5c74 to finish@-@{"workflow": "Project WH Parallel Datapipeline", "task-id": "delete dat
aproc_cluster", "execution-date": "2021-01-22T00:00:00+00:00"}
[2021-01-23 07:24:05,630] {gcp dataproc hook.py:275} INFO - Dataproc Operation projects/
dataproc-300110/regions/us-east1/operations/1bd8742b-14a7-34dd-b139-675c21a35c74 done@-@
{"workflow": "Project WH Parallel Datapipeline", "task-id": "delete dataproc cluster", "
execution-date": "2021-01-22T00:00:00+00:00"}
[2021-01-23 07:24:05,784] {taskinstance.py:1071} INFO - Marking task as SUCCESS.dag id=P
roject_WH_Parallel_Datapipeline, task_id=delete_dataproc_cluster, execution_date=2021012
2T000000, start date=20210123T072332, end date=20210123T072405
[2021-01-23 07:24:07,491] {local task job.py:102} INFO - Task exited with return code 0
```

3.4 Viewing the DAG Graph View in Apache Airflow

The following Figure shows the graph view of the workflow.

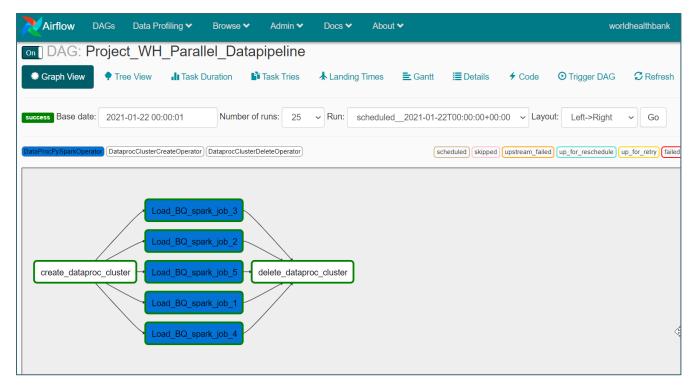


Figure 5:Graph View

3.5 Viewing the DAG Gantt View in Apache Airflow

The following figure shows the Gantt view of the workflow. Note the parallel processing of jobs. Had these jobs been run sequentially more time would have taken for running the workflow.



Figure 6: Gantt View

3.6 Tables loaded in Bigquery

The following Figure shows the tables loaded in bigquery. We are particularly interested in the wh health nutrition population table. This is a partitioned and clustered table.

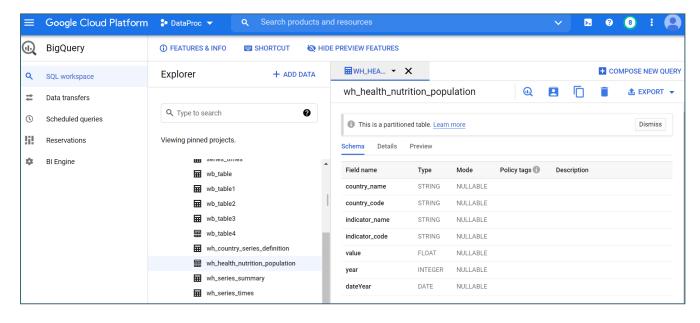


Figure 7: Tables loaded in Bigquery

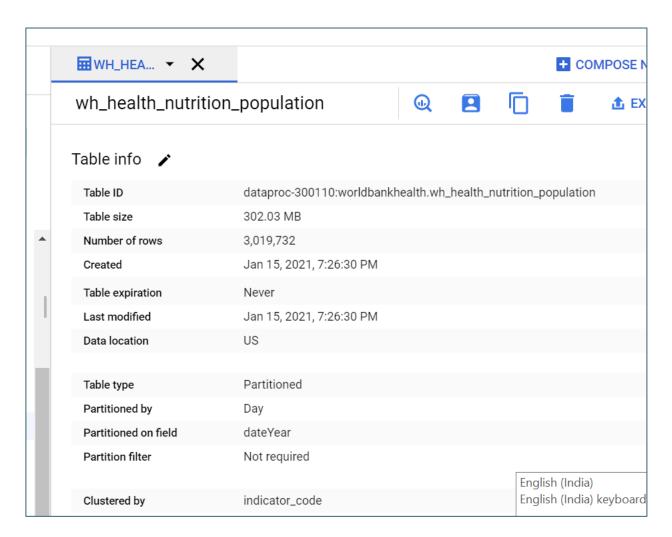


Figure 8: Table loaded - Partitioned and Clustered

Visualizations using Datalab

Visualizations were done using Datalab.

The following jupiter notebook was created and visualizations generated from the bigquery tables. Alternatively the jupiter notebook has been uploaded in the following location:

https://github.com/Sadiya-Dalvi/GoogleComposer/blob/main/GH-Project-Corr.ipynb

```
import seaborn as sn
import matplotlib.pyplot as plt
import pandas as pd
%load_ext google.cloud.bigquery
```

What is the average age of males and females in different countries around the world.

As there is no direct way to calculate average age, the below approach is taken:

We have indicator codes like 'SP.POP.%.MA.5Y' which give us % population between each 5Y band from age 0 to age 80+ example codes are SP.POP.10-14.MA.5Y, SP.POP.45-49.MA.5Y

Below query extracts the starting age of each 5Y block and adds 2.5 to it to get the average age We already have the % population in that age band as value field. This is added up for each country to get the average age in each country:

```
%%bigquery df_avg_age
SELECT round(sum(((cast(substr(indicator_code,8,2) as INT64) + 2.5) * value))/100,2) as Av
g_AGE , country_code, country_name
FROM `bigquery-public-data.world_bank_health_population.health_nutrition_population`
where indicator_code like 'SP.POP.%.MA.5Y' and year = 2019
group by country_code, country_name
order by Avg_AGE DESC
```

Top 20 countries with highest Average Ages

```
%%bigquery df_avg_age
SELECT round(sum(((cast(substr(indicator_code,8,2) as INT64) + 2.5) * value))/100,2) as Av
g_AGE , country_code, country_name
FROM `bigquery-public-data.world_bank_health_population.health_nutrition_population`
```

Author: Sadiya Dalvi GHCI TechPathWays - Data Engineering Program

where indicator_code like 'SP.POP.%.MA.5Y' and year = 2019 group by country_code, country_name order by Avg_AGE DESC limit 20

df_avg_age.plot(kind="bar", x="country_name", y="Avg_AGE")

<matplotlib.axes._subplots.AxesSubplot at 0x7faa79ecb358>

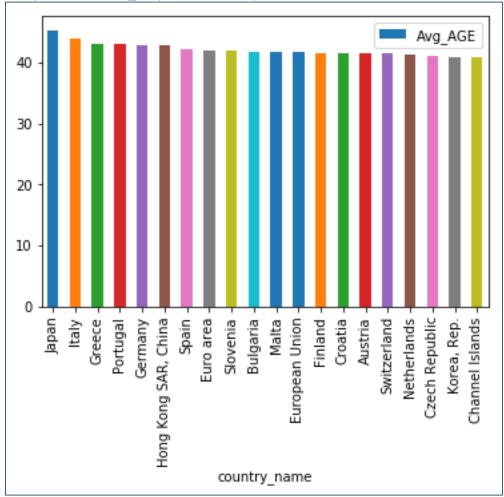


Figure 9: Highest Average Age across the world

df_avg_age.describe()

	Avg_AGE
count	20.000000
mean	42.175500
std	1.107099
min	40.890000

	Avg_AGE
25%	41.535000
50%	41.795000
75%	42.950000
max	45.350000

20 countries with lowest Average Ages

```
%%bigquery df_avg_age
SELECT round(sum(((cast(substr(indicator_code,8,2) as INT64) + 2.5) * value))/100,2) as Av
g_AGE , country_code, country_name
FROM `bigquery-public-data.world_bank_health_population.health_nutrition_population`
where indicator_code like 'SP.POP.%.MA.5Y' and year = 2019
group by country_code, country_name
order by Avg_AGE ASC limit 20

df_avg_age.plot(kind="bar", x="country_name", y="Avg_AGE")
<matplotlib.axes._subplots.AxesSubplot at 0x7faa78adba58>
```

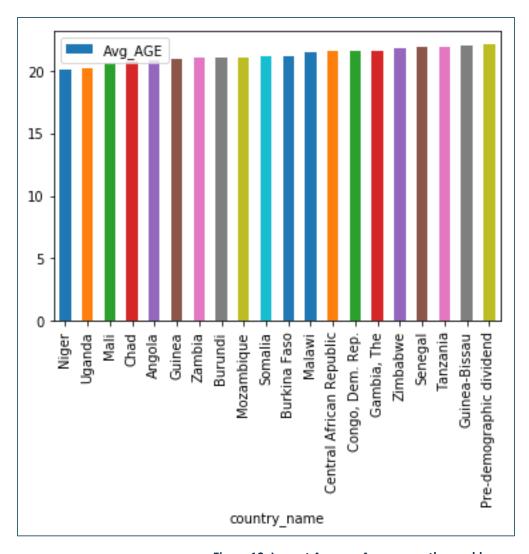


Figure 10: Lowest Average Ages across the world

Correlation between Health Expenditure and survival ages in the two genders around the world

%%bigquery survival_male select value as survival_male_65, country_name, year from dataproc-300110.worldbankhealth.health_nutrition_population where indicator_code in ('SP.DYN.TO65.MA.ZS') and year > 2000

```
%%bigquery health_exp
select value as health_exp, country_name, year
from dataproc-300110.worldbankhealth.health_nutrition_population
where indicator code in ('SH.XPD.CHEX.PC.CD') and year > 2000
```

```
merge_pd = pd.merge(survival_male, health_exp, on=['country_name','year'])

corr_df = merge_pd

corr_df.drop(['year', 'country_name'], inplace=True, axis='columns')

corrMatrix = corr_df.corr()

sn.heatmap(corrMatrix,cmap='RdBu', center=0, annot=True)

plt.savefig('heathexp_survival_male_correlation.png')

plt.show()
```

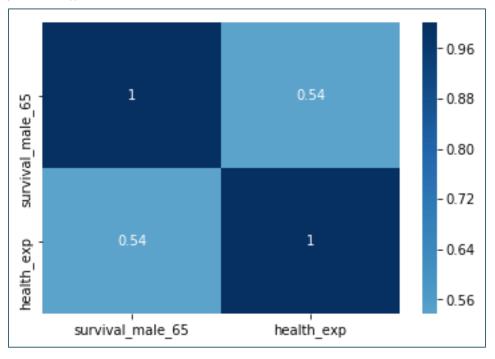


Figure 11: Correlation between Health Expenditure and Survival Ages of Males

```
%*bigquery survival_female
select value as survival_female_65, country_name, year
from dataproc-300110.worldbankhealth.health_nutrition_population
where indicator_code in ('SP.DYN.T065.FE.ZS') and year > 2000

merge_pd = pd.merge(survival_female, health_exp, on=['country_name','year'])
corr_df = merge_pd

corr_df.drop(['year', 'country_name'], inplace=True, axis='columns')
corrMatrix = corr_df.corr()
sn.heatmap(corrMatrix,cmap='RdBu', center=0, annot=True)
plt.savefig('heathexp_survival_female_correlation.png')
plt.show()
```

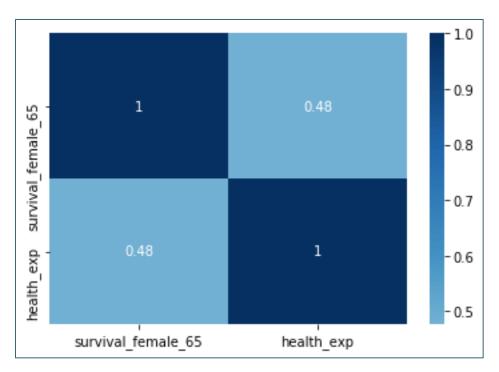


Figure 122: Correlation between Health Expenditure and Survival Ages of Females

Correlation between School enrollment and unemployment for males and females

School enrollment, secondary, male (% net) - SE.SEC.NENR.MA Unemployment, male (% of male labor force) - SL.UEM.TOTL.MA.ZS

```
%bigquery df_school_enroll
select value as school_enroll, country_name, year
from dataproc-300110.worldbankhealth.health_nutrition_population
where indicator_code in ('SE.SEC.NENR.MA') and year > 2000

%bigquery df_unemploy
select value as unemploy, country_name, year
from dataproc-300110.worldbankhealth.health_nutrition_population
where indicator_code in ('SL.UEM.TOTL.MA.ZS') and year > 2000

merge_pd = pd.merge(df_school_enroll, df_unemploy, on=['country_name','year'])

corr_df = merge_pd

corr_df.drop(['year', 'country_name'], inplace=True, axis='columns')
corrMatrix = corr_df.corr()
sn.heatmap(corrMatrix,cmap='RdBu', center=0, annot=True)
```

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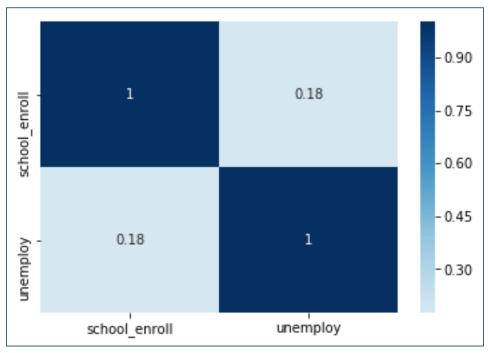


Figure 132: Correlation between School Enrollment and Unemployment of Males

Correlation between School enrollment and unemployment for females Using the below indicator code / indicator names

School enrollment, secondary, female (% net) - SE.SEC.NENR.FE Unemployment, female (% of female labor force) - SL.UEM.TOTL.FE.ZS

```
%%bigquery df_school_enroll
select value as school_enroll, country_name, year
from dataproc-300110.worldbankhealth.health_nutrition_population
where indicator_code in ('SE.SEC.NENR.FE') and year > 2000

%%bigquery df_unemploy
select value as unemploy, country_name, year
from dataproc-300110.worldbankhealth.health_nutrition_population
where indicator_code in ('SL.UEM.TOTL.FE.ZS') and year > 2000
merge_pd = pd.merge(df_school_enroll, df_unemploy, on=['country_name','year'])
corr_df = merge_pd
corr_df.drop(['year', 'country_name'], inplace=True, axis='columns')
```

```
corrMatrix = corr_df.corr()
sn.heatmap(corrMatrix,cmap='RdBu', center=0, annot=True)
plt.savefig('male_schoo_enroll_unemploy.png')
plt.show()
```

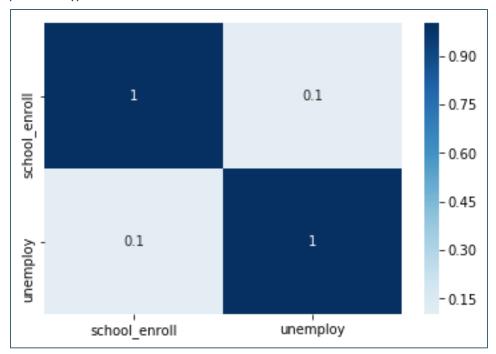


Figure 142: Correlation between School Enrollment and Unemployment of Females

Average age of first pregnancy around the world

Since the above indicator was not present in the dataset, the following assumptions are made:

Average age of first pregnancy is estimated as the average age of first marriage + 2. The indicator for age at first marriage, female - SP.DYN.SMAM.FE is available in the dataset

```
%%bigquery df_first_preg
SELECT round(value+2,1) as First_Pregnancy , country_code, country_name, year
FROM `dataproc-300110.worldbankhealth.wh_health_nutrition_population`
where indicator_code like 'SP.DYN.SMAM.FE' and year = 2013 and value > 15
order by value desc

df_first_preg.plot(kind="bar", x="country_name", y="First_Pregnancy")
<matplotlib.axes._subplots.AxesSubplot at 0x7faa78b49048>
```

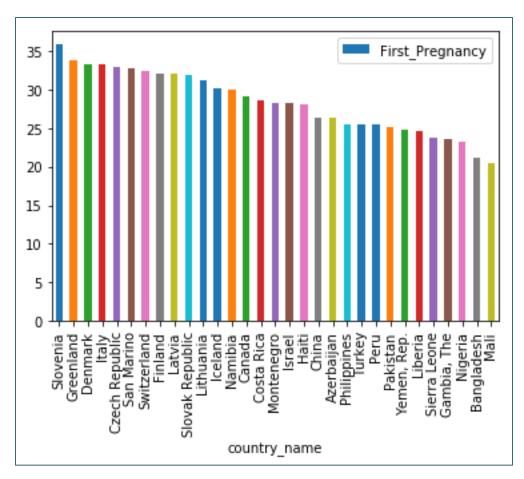


Figure 152: Average Age of First Pregnancy across the world

Analysis of age of marriage and infant mortality rate across different demographics

Mortality rate, infant (per 1,000 live births) – Indicator code is SP.DYN.IMRT.IN

Age of First marriage – Indicator code is 'SP.DYN.SMAM.FE'

%%bigquery df_mortality

SELECT round(value,1) as infant_mortality , country_code, country_name, year FROM `dataproc-300110.worldbankhealth.wh_health_nutrition_population` where indicator_code like 'SP.DYN.IMRT.IN' and year = 2013 order by value desc

df_mortality.describe()

	infant_mortality	year
count	234.000000	234.0

	infant_mortality	year
mean	25.038889	2013.0
std	21.528964	0.0
min	3.000000	2013.0
25%	6.725000	2013.0
50%	17.350000	2013.0
75%	38.375000	2013.0
max	96.600000	2013.0

%%bigquery df_first_marriage

SELECT round(value,1) as first_marriage , country_code, country_name, year FROM `dataproc-300110.worldbankhealth.wh_health_nutrition_population` where indicator_code like 'SP.DYN.SMAM.FE' and year = 2013 and value > 15 order by value desc

df_marriage_mortality = pd.merge(df_first_marriage, df_mortality, on=['country_name','year
'])

df_marriage_mortality.plot(kind='bar',x='country_name',y=['first_marriage', 'infant_mortal
ity'], secondary_y= 'infant_mortality')

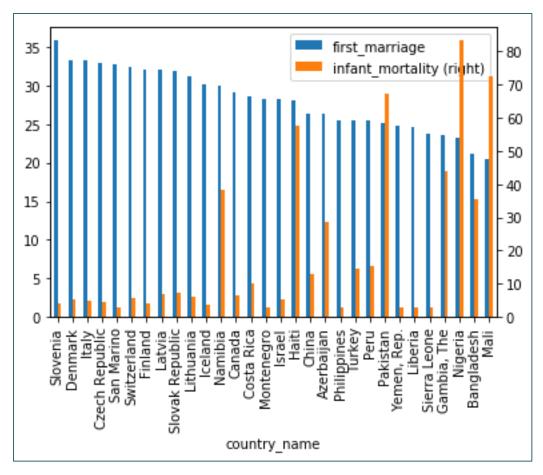


Figure 16: Age of marriage and infant mortality rate

3.7 Performance Comparison observed in BigQuery

In this section, we will compare the queries mentioned in the assignment with the raw dataset and the etl table.

Query	Raw Data Timings bigquery-public- data.world_bank_health_populat ion.health_nutrition_populatio n age of males and females in diff	Optimized ETL Table Timings dataproc- 300110.worldbankhealth.wh_health_nutrition_popul ation ferent countries around the world	
SELECT round(sum(((ca st(substr(indicator_c ode,8,2) as INT64) + 2.5) * value))/100,2) as Avg_AGE , country_code, country_name FROM ` dataproc-30011 0.worldbankhealth.wh_health_nutrition_population ` where indicator_code like 'SP.POP.%.MA.5Y' and year = 2019 group by country_code , country_name order by Avg_AGE DESC	Query complete (0.8 sec elapsed, 149.3 MB processed)	Query complete (0.8 sec elapsed, 2.4 MB processed)	
Correlation between Health Expenditure and survival ages in the two genders around the world			
select value as survival_male_65, country_name, year from dataproc- 300110.worldbankhealt h.wh_health_nutrition _population where indicator_code in ('SP.DYN.TO65.MA.ZS') and year > 2000	Query complete (0.8 sec elapsed, 134.9 MB processed)	Query complete (0.5 sec elapsed, 52.8 MB processed)	
select value as health_exp, country_name, year from dataproc-300110.worldbankhealt h.wh_health_nutrition _population where indicator_code in ('SH.XPD.CHEX.PC.CD') and year > 2000	Query complete (0.4 sec elapsed, 134.9 MB processed)	Query complete (0.4 sec elapsed, 52.3 MB processed)	

select value as survival_female_65, country_name, year from dataproc- 300110.worldbankhealt h.wh_health_nutrition _population where indicator_code in ('SP.DYN.TO65.FE.ZS') and year > 2000	Query complete (0.3 sec elapsed, 134.9 MB processed)	Query complete (0.3 sec elapsed, 52.8 MB processed)
---	--	---

Correlation between School enrollment and unemployment for males and females around the world

select value as school_enroll, country_name, year from dataproc- 300110.worldbankhealt h.wh_health_nutrition _population where indicator_code in ('SE.SEC.NENR.MA') and year > 2000	Query complete (0.6 sec elapsed, 134.9 MB processed)	Query complete (0.4 sec elapsed, 50 MB processed)
select value as unemploy, country_name, year from dataproc-300110.worldbankhealt h.wh_health_nutrition _population where indicator_code in ('SL.UEM.TOTL.MA.ZS') and year > 2000	Query complete (0.5 sec elapsed, 134.9 MB processed)	Query complete (0.3 sec elapsed, 52.3 MB processed)
select value as school_enroll, country_name, year from dataproc- 300110.worldbankhealt h.wh_health_nutrition _population where indicator_code in ('SE.SEC.NENR.FE') and year > 2000	Query complete (0.7 sec elapsed, 134.9 MB processed)	Query complete (0.4 sec elapsed, 50 MB processed)
select value as unemploy, country_name, year from dataproc- 300110.worldbankhealt h.wh_health_nutrition _population where indicator_code in ('SL.UEM.TOTL.FE.ZS') and year > 2000	Query complete (0.4 sec elapsed, 134.9 MB processed)	Query complete (0.3 sec elapsed, 52.3 MB processed)

Average age of first pregnancy around the world			
SELECT round(value+2,1) as First_Pregnancy, country_code, country_name, year FROM `dataproc- 300110.worldbankhealt h.wh_health_nutrition _population` where indicator_code like 'SP.DYN.SMAM.FE' and year = 2013 and value > 15 order by value desc	Query complete (0.3 sec elapsed, 149.3 MB processed)	Query complete (0.5 sec elapsed, 3.2 MB processed)	
Analysis of age of marriage and infant mortality rate across different demograpics			
SELECT round(value,1) as infant_mortality, country_code, country_name, year FROM `dataproc- 300110.worldbankhealt h.wh_health_nutrition _population` where indicator_code like 'SP.DYN.IMRT.IN' and year = 2013 order by value desc	Query complete (0.4 sec elapsed, 149.3 MB processed)	Query complete (0.3 sec elapsed, 3.2 MB processed)	
SELECT round(value,1) as first_marriage, country_code, country_name, year FROM `dataproc- 300110.worldbankhealt h.wh_health_nutrition _population` where indicator_code like 'SP.DYN.SMAM.FE' and year = 2013 and value > 15 order by value desc	Query complete (0.3 sec elapsed, 149.3 MB processed)	Query complete (0.2 sec elapsed, 3.2 MB processed)	