

## 1. Requirement and Specification

A Health Care insurance company is facing challenges in enhancing its revenue and understanding the customers. To address these challenges, the company aims to leverage the Big Data Ecosystem to analyze competitors' company data received from various sources, such as web scraping and third-party sources. This analysis will help track customer behavior and conditions, enabling the company to customize offers and calculate royalties for customers who have previously purchased policies, thereby enhancing revenue.

### Project Goals

The primary goal of this project is to create data pipelines for the Health Care insurance company. These pipelines will enable the company to:

- Analyze customer behaviors.
- Send customized offers to customers.
- Calculate and distribute royalties to past customers.
- Develop appropriate business strategies to enhance revenue.

MoreDetails:

<https://github.com/eshrestha21/Health-Care-insurance-Company-Analysis/blob/main/Requirements%20Specifications%20Document.pdf>

## 2. Solution Design

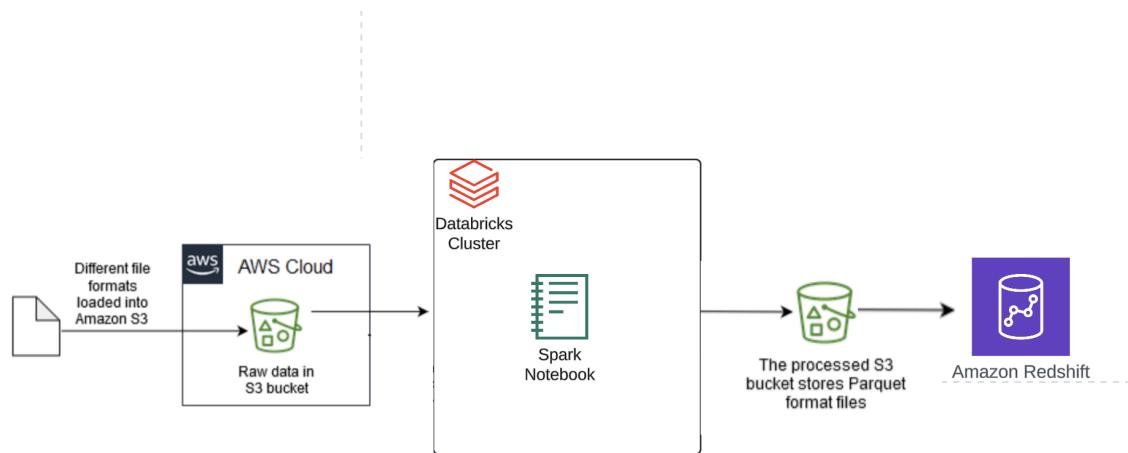
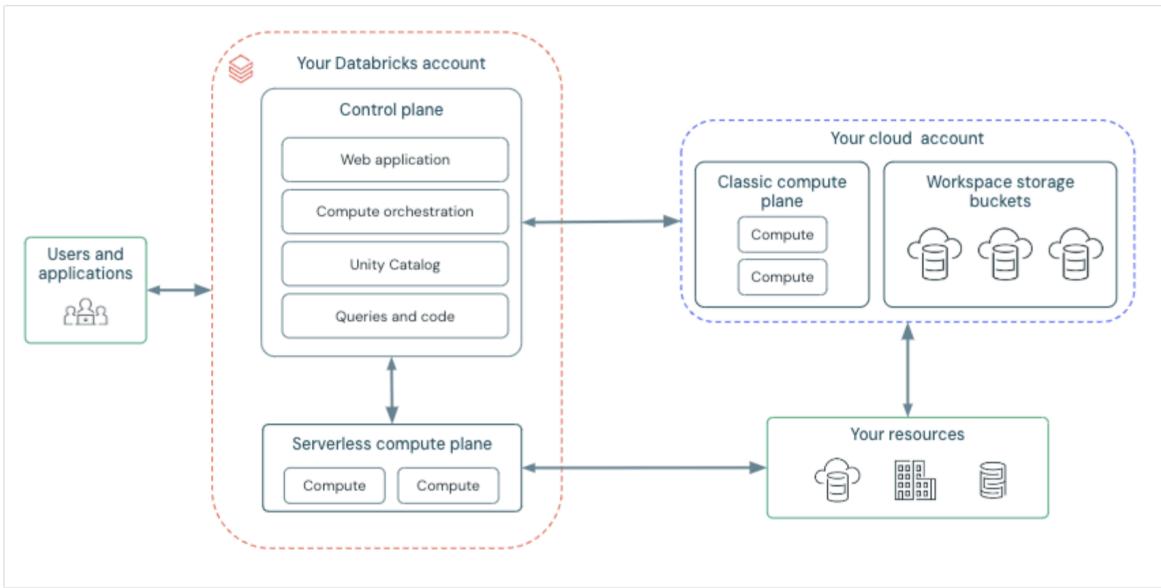


Figure: Architecture Diagram to create data pipelines for the Health Care insurance company

The following diagram describes the overall Databricks architecture.



Details:

<https://github.com/eshrestha21/Health-Care-insurance-Company-Analysis/blob/main/Solution%20Design%20Document.pdf>

### 3. Environment

- **AWS S3:** Data storage for raw and processed data
- **AWS Redshift:** Data warehousing for analysis and reporting
- **Databricks:** Data processing and analysis platform
- **PySpark:** Distributed data processing framework
- **GitHub:** Version control and code repository
- **Jira:** Project management and tracking
- **AWS EMR Studio:** For deployment (optional)

### 4. Requirements

- **Disease Analysis:** Identify the disease with the maximum number of claims.
- **Subscriber Analysis:** Find subscribers under the age of 30 who subscribe to any subgroup.
- **Group Analysis:** Determine which group has the maximum number of subgroups.
- **Hospital Analysis:** Identify the hospital that serves the most number of patients.
- **Subgroup Analysis:** Find out which subgroup is subscribed to the most.
- **Claims Rejection Analysis:** Calculate the total number of claims that were rejected.
- **Claims Origin Analysis:** Determine the city from which most claims are coming.
- **Policy Type Analysis:** Identify whether subscribers mostly subscribe to government or private policies.

- **Premium Analysis:** Calculate the average monthly premium paid by subscribers to the insurance company.
- **Profitability Analysis:** Find out which group is most profitable.
- **Pediatric Cancer Patients:** List all patients below age 18 who are admitted for cancer.
- **High-Value Cashless Insurance Patients:** List patients who have cashless insurance and total charges greater than or equal to Rs. 50,000.
- **Female Knee Surgery Patients:** List female patients over the age of 40 that have undergone knee surgery in the past year.

## 5. Project Management - JIRA

This entire project can be managed using Jira(project tracking tool), breaking it down into 2 week sprints. The first week focuses on documentation and solution design, while the second week is dedicated to implementation and testing. Each use case and test scenario is tracked as a Jira user story or task, allowing us to monitor progress and manage resources effectively.

I have created a scrum project in JIRA - Healthcare Analysis with a 2 week sprint. Created a major Epic as - Healthcare Data Analysis. Then user stories and tasks are added under each epic such as Requirement, Design Document, Data Cleaning, Analysis and so on. Jira's board view to track progress

The screenshot shows a Jira Scrum board titled "Sprint 1- Healthcare Analysis". The board is divided into four columns: TO DO, IN PROGRESS, DONE, and TESTING. The DONE and TESTING columns are currently active, showing completed work items. The board includes a sidebar with project navigation and a search bar at the top.

Column	User Stories / Tasks
TO DO	Design database schema for AWS Redshift, HCDP-10; Design data processing pipeline, HCDP-13; Database Schema Design, HCDP-15; Define tables and relationships for disease analysis, HCDP-16; Implement hospital analysis module, HCDP-20
IN PROGRESS	Solution Design Document, HCDP-7; Create high-level architecture diagrams, HCDP-9; Solution Design, HCDP-11; Data Analysis, HCDP-18; Implement subscriber analysis module, HCDP-21
DONE	Review the requirement specification document with stakeholders, HCDP-6; Implement disease analysis module, HCDP-19; Design data storage and retrieval mechanisms, HCDP-14; Implement group analysis module, HCDP-21
TESTING	Requirement Specification Document, HCDP-1; Design data pipelines architecture, HCDP-8; Design data ingestion pipeline, HCDP-12

## 6. Github

Throughout this process, I have maintained comprehensive documentation, including our requirement specifications, solution design documents, and database schema designs. All our PySpark code for data cleansing and result generation is version-controlled and stored in a GitHub repository. This ensures transparency, reproducibility, and ease of collaboration for our team.

<https://github.com/eshrestha21/Health-Care-insurance-Company-Analysis>

<https://databricks-prod-cloudfront.cloud.databricks.com/public/4027ec902e239c93eaaa8714f173bcfc/1166544219295246/2435706089467460/8156463845699645/latest.html>

## 7. Dataset Creation

Here, the data resides in AWS S3. I am leveraging the power of Databricks to ingest this data efficiently. Using PySpark, I have established a secure connection to our S3 bucket and read the various datasets - patients, subscribers, claims, and group\_subgroup - into Databricks DataFrames. This step sets the foundation for our entire data pipeline.

**Environment:** Databricks, PySpark, AWS S3

# Data stored in AWS S3

Amazon S3 > Buckets > health-insurance-capstone

**Objects (3) info**

Name	Type	Last modified	Size	Storage class
clean-data/	Folder	-	-	-
query-result/	Folder	-	-	-
raw-data/	Folder	-	-	-

Amazon S3 > Buckets > health-insurance-capstone > raw-data/

**Objects (8) info**

Name	Type	Last modified	Size	Storage class
claims.json	json	July 10, 2024, 16:35:27 (UTC-05:00)	13.1 KB	Standard
disease.csv	csv	July 10, 2024, 16:35:27 (UTC-05:00)	1.5 KB	Standard
group.csv	csv	July 10, 2024, 16:35:27 (UTC-05:00)	4.6 KB	Standard
grsubgrp.csv	csv	July 10, 2024, 16:35:28 (UTC-05:00)	473.0 B	Standard
hospital.csv	csv	July 10, 2024, 16:35:28 (UTC-05:00)	1.3 KB	Standard
Patient_records.csv	csv	July 10, 2024, 16:35:29 (UTC-05:00)	5.0 KB	Standard
subgroup.csv	csv	July 10, 2024, 16:35:29 (UTC-05:00)	263.0 B	Standard
subscriber.csv	csv	July 10, 2024, 16:35:29 (UTC-05:00)	11.7 KB	Standard

## # Accessing the AWS Bucket

```
▶ ✓ 02:21 PM (<1s)
#Import libraries
from pyspark.sql import SparkSession, Row
from pyspark.sql.functions import col, count, avg, when, year, datediff, current_date, avg, sum, count
from pyspark.sql.types import IntegerType

# Initialize Spark session
spark = SparkSession.builder \
    .appName("Health Insurance Analysis") \
    .getOrCreate()
```

```
▶ ✓ 02:21 PM (<1s)
4
# Accessing the AWS Bucket
access_key = 'XXXXXXXXXXXX'
secret_key = 'XXXXXXXX+xIP9o/I'
sc._jsc.hadoopConfiguration().set("fs.s3a.access.key", access_key)
sc._jsc.hadoopConfiguration().set("fs.s3a.secret.key", secret_key)

# If you are using Auto Loader file notification mode to load files, provide the AWS Region ID.
aws_region = "us-east-2"
sc._jsc.hadoopConfiguration().set("fs.s3a.endpoint", "s3." + aws_region + ".amazonaws.com")
```

## #ExtractLoad Data in Databricks from AWS S3

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```

# Load the data from AWS S3
claims_df = spark.read.json("s3a://health-insurance-capstone/raw-data/claims.json")
disease_df = spark.read.csv("s3a://health-insurance-capstone/raw-data/disease.csv", header=True, inferSchema=True)
group_df = spark.read.csv("s3a://health-insurance-capstone/raw-data/group.csv", header=True, inferSchema=True)
grpsubgrp_df = spark.read.csv("s3a://health-insurance-capstone/raw-data/grpsubgrp.csv", header=True, inferSchema=True)
subgroup_df = spark.read.csv("s3a://health-insurance-capstone/raw-data/subgroup.csv", header=True, inferSchema=True)
subscriber_df = spark.read.csv("s3a://health-insurance-capstone/raw-data/subscriber.csv", header=True, inferSchema=True)
patient_records_df = spark.read.csv("s3a://health-insurance-capstone/raw-data/Patient_records.csv", header=True, inferSchema=True)

(15) Spark Jobs
claims_df: pyspark.sql.dataframe.DataFrame = [Claim_Or_Rejected: string, SUB_ID: string ... 6 more fields]
disease_df: pyspark.sql.dataframe.DataFrame = [SubGrpID: string, Disease_ID: integer ... 1 more field]
group_df: pyspark.sql.dataframe.DataFrame = [Country: string, premium_written: integer ... 6 more fields]
grpsubgrp_df: pyspark.sql.dataframe.DataFrame = [SubGrp_ID: string, Grp_Id: string]
hospital_df: pyspark.sql.dataframe.DataFrame = [Hospital_Id: string, Hospital_name: string ... 3 more fields]
subgroup_df: pyspark.sql.dataframe.DataFrame = [SubGrp_ID: string, SubGrp_Name: string ... 1 more field]
subscriber_df: pyspark.sql.dataframe.DataFrame = [sub_Id: string, first_name: string ... 12 more fields]
patient_records_df: pyspark.sql.dataframe.DataFrame = [Patient_Id: integer, Patient_name: string ... 6 more fields]

```

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```

# EXTRACT DATA FROM AWS S3
# Reading the data from AWS S3
claims_df = spark.read.json("s3a://health-insurance-capstone/raw-data/claims.json")
disease_df = spark.read.csv("s3a://health-insurance-capstone/raw-data/disease.csv", header=True, inferSchema=True)
group_df = spark.read.csv("s3a://health-insurance-capstone/raw-data/group.csv", header=True, inferSchema=True)
grpsubgrp_df = spark.read.csv("s3a://health-insurance-capstone/raw-data/grpsubgrp.csv", header=True, inferSchema=True)
hospital_df = spark.read.csv("s3a://health-insurance-capstone/raw-data/hospital.csv", header=True, inferSchema=True)
subgroup_df = spark.read.csv("s3a://health-insurance-capstone/raw-data/subgroup.csv", header=True, inferSchema=True)
subscriber_df = spark.read.csv("s3a://health-insurance-capstone/raw-data/subscriber.csv", header=True, inferSchema=True)
patient_records_df = spark.read.csv("s3a://health-insurance-capstone/raw-data/Patient_records.csv", header=True, inferSchema=True)

(15) Spark Jobs
claims_df: pyspark.sql.dataframe.DataFrame
  Claim_Or_Rejected: string
  SUB_ID: string
  claim_amount: string
  claim_date: string
  claim_id: long
  claim_type: string
  disease_name: string
  patient_id: long
disease_df: pyspark.sql.dataframe.DataFrame
  SubGrpID: string
  Disease_ID: integer
  Disease_name: string
group_df: pyspark.sql.dataframe.DataFrame
  Country: string
  premium_written: integer
  zipcode: integer
  Grp_Id: string
  Grp_Name: string
  Grp_Type: string
  ...

```

Just now (1s)

```

# Print schema and display data for each DataFrame
print("Schema of claims_df:")
claims_df.printSchema()
claims_df.show()

(1) Spark Jobs
Schema of claims_df:
root
 |-- Claim_Or_Rejected: string (nullable = true)
 |-- SUB_ID: string (nullable = true)
 |-- claim_amount: string (nullable = true)
 |-- claim_date: string (nullable = true)
 |-- claim_id: long (nullable = true)
 |-- claim_type: string (nullable = true)
 |-- disease_name: string (nullable = true)
 |-- patient_id: long (nullable = true)

+-----+-----+-----+-----+-----+-----+
|Claim_Or_Rejected|SUB_ID|claim_amount|claim_date|claim_id|claim_type|
+-----+-----+-----+-----+-----+-----+
|N|SUBID1000|79874|1949-03-14|0|claims of value|Galactosemia|187158|
|NaN|SUBID10001|151142|1970-03-16|1|claims of policy|Bladder cancer|112766|
|NaN|SUBID10002|59924|2008-02-03|2|claims of value|Kidney cancer|199252|
|NaN|SUBID10003|143120|1995-02-08|3|claims of fact|Suicide|133424|
|Y|SUBID10004|168634|1967-05-23|4|claims of value|Food allergy|172579|
|NaN|SUBID10005|64840|1991-10-04|5|claims of policy|Whiplash|171328|
|N|SUBID10006|26880|1991-03-26|6|claims of fact|Sunbathing|107794|

```

Just now (<1s) 8 Python

```
# Print schema and display data for each DataFrame
print("Schema of disease_df:")
disease_df.printSchema()
disease_df.show()

▶ (1) Spark Jobs
```

Schema of disease\_df:

SubGrpID	Disease_ID	Disease_name
S101	110001	Beriberi
S101	110002	Scurvy
S101	110003	Goitre
S101	110004	Osteoporosis
S101	110005	Rickets
S101	110006	Anaemia
S102	110007	Fractures
S102	110008	Heart Attack
S102	110009	Burns
S102	110010	Choking
S102	110011	Stroke

Just now (<1s) 8

```
# Print schema and display data for each DataFrame
print("Schema of group_df:")
group_df.printSchema()
group_df.show()

▶ (1) Spark Jobs
```

Schema of group\_df:

Country	premium_written	zipcode	Grp_Id	Grp_Name	Grp_Type	city	year
India	72000	482018	GRP101	Life Insurance Co...	Govt.	Mumbai	1956
India	45000	482049	GRP102	HDFC Standard Lif...	Private	Mumbai	2000
India	64000	482030	GRP103	Max Life Insuranc...	Private	Delhi	2000
India	59000	482028	GRP104	ICICI Prudential ...	Private	Mumbai	2000
India	37000	482014	GRP105	Kotak Mahindra Li...	Private	Mumbai	2001
India	89000	482011	GRP106	Aditya Birla Sun ...	Private	Mumbai	2000
India	70000	482006	GRP107	TATA AIG Life Ins...	Private	Mumbai	2001

Just now (<1s)

```
print("Schema of hospital_df:")
hospital_df.printSchema()
hospital_df.show()
```

▶ (1) Spark Jobs

Schema of hospital\_df:

root

```
|-- Hospital_id: string (nullable = true)
|-- Hospital_name: string (nullable = true)
|-- city: string (nullable = true)
|-- state: string (nullable = true)
|-- country: string (nullable = true)
```

Hospital_id	Hospital_name	city	state	country
H1000	All India Institu...	New Delhi	Nan	India
H1001	Medanta The Medicity	Gurgaon	Haryana	India
H1002	The Christian Med...	Vellore	Tamil Nadu	India
H1003	PGIMER – Postgrad...	Chandigarh	Haryana	India
H1004	Apollo Hospital -...	Chennai	Tamil Nadu	India
H1005	P. D. Hinduja Nat...	Mumbai	Maharashtra	India
H1006	Breach Candy Hosp...	Mumbai	Maharashtra	India
H1007	Fortis Flt. Lt. R...	New Delhi	Nan	India
H1008	King Edward Memor...	Mumbai	Maharashtra	India
H1009	Indraprastha Aopol...	Delhi	Nan	India

Just now (<1s)

```
print("Schema of subgroup_df:")
subgroup_df.printSchema()
subgroup_df.show()
```

▶ (1) Spark Jobs

Schema of subgroup\_df:

root

```
|-- SubGrp_id: string (nullable = true)
|-- SubGrp_Name: string (nullable = true)
|-- Monthly_Premium: integer (nullable = true)
```

SubGrp_id	SubGrp_Name	Monthly_Premium
S101	Deficiency Diseases	3000
S102	Accident	1000
S103	Physiology	2000
S104	Therapy	1500
S105	Allergies	2300
S106	Self inflicted	1200
S107	Cancer	3200
S108	Infectious disease	1500
S109	Hereditary	2000
S110	Viral	1000

```

print("Schema of subscriber_df:")
subscriber_df.printSchema()
subscriber_df.show()

+---+---+---+---+---+
| sub _id|first_name| last_name|      Street|Birth_date|Gender|      Phone|Country|
+---+---+---+---+---+
|SUBID10000| Harbir|Vishwakarma| Baria Marg|1924-06-30|Female|+91 0112009318| India|
|SUBID10001| Brahmdev| Sonkar| Lala Marg|1948-12-20|Female|+91 1727749552| India|
+---+---+---+---+---+

```

```

print("Schema of patient_records_df:")
patient_records_df.printSchema()
patient_records_df.show()

+---+---+---+---+---+---+---+
|Patient_id|Patient_name|patient_gender|patient_birth_date| patient_phone| disease_name| city|hospital_id|
+---+---+---+---+---+---+---+
| 187158| Harbir| Female| 1924-06-30|+91 0112009318| Galactosemia| Rourkela| H1001|
| 112766| Brahmdev| Female| 1948-12-20|+91 1727749552| Bladder cancer| Tiruvottiyur| H1016|
| 199252| Ujawal| Male| 1980-04-16|+91 8547451606| Kidney cancer| Berhampur| H1009|
| 133424| Ballari| Female| 1969-09-25|+91 9166826841| Suicide| Bihar Sharif| H1017|
| 172579| Devnath| Female| 1946-05-01|+91 1868774631| Food allergy| Bidhanagar| H1019|
| 171320| Atasi| Male| 1967-10-02|+91 9747336855| Whiplash| Amravati| H1013|
| 1077941| Manish| Male| 1967-06-06|+91 43542940431| Sunbathingol| Panvel| H1004|
+---+---+---+---+---+---+---+

```

## 8. Data Cleaning

Data cleaning is the process of fixing or removing incorrect, corrupted, incorrectly formatted, duplicate, or incomplete data within a dataset. When combining multiple data sources, there are many opportunities for data to be duplicated or mislabeled. If data is incorrect, outcomes and algorithms are unreliable, even though they may look correct. There is no one absolute way to prescribe the exact steps in the data cleaning process because the processes will vary from dataset to dataset.

- Cleaning Activity
  - First check if there are null values in dataset
  - Count the total Null values for each column
  - And then replace the null values for specific columns by NA
  - Check the If three are duplicates records
  - If there are duplicates then drop duplicates

```

# TRANSFORM DATA

# Function to clean a DataFrame
def clean_data(df, df_name):
    # 1. Replace empty strings with None (null)
    df = df.replace("", None)

    # 2. Check for null values and count them for each column
    null_counts = df.select([count(when(col(c).isNull(), c)).alias(c) for c in df.columns])
    null_counts.show()

    # 3. Replace remaining null values with 'NA' for specific columns (customize as needed)
    columns_to_replace = df.columns
    df = df.fillna("NA", subset=columns_to_replace)

    # 4. Check for duplicates and drop duplicates
    initial_count = df.count()
    df = df.dropDuplicates()
    final_count = df.count()

    print(f"Number of duplicates dropped in {df_name}: {initial_count - final_count}")

return df

```

```

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# Clean each DataFrame using user defined function clean_data()
claims_df_cleaned = clean_data(claims_df, "claims_df")
disease_df_cleaned = clean_data(disease_df, "disease_df")
group_df_cleaned = clean_data(group_df, "group_df")
grpsubgrp_df_cleaned = clean_data(grpsubgrp_df, "grpsubgrp_df")
hospital_df_cleaned = clean_data(hospital_df, "hospital_df")
subgroup_df_cleaned = clean_data(subgroup_df, "subgroup_df")
subscriber_df_cleaned = clean_data(subscriber_df, "subscriber_df")
patient_records_df_cleaned = clean_data(patient_records_df, "patient_records_df")

▶ (56) Spark Jobs
▶ claims_df_cleaned: pyspark.sql.dataframe.DataFrame = [Claim_Or_Rejected: string, SUB_ID: string ... 6 more fields]
▶ disease_df_cleaned: pyspark.sql.dataframe.DataFrame = [SubGrpID: string, Disease_ID: integer ... 1 more field]
▶ group_df_cleaned: pyspark.sql.dataframe.DataFrame = [Country: string, premium_written: integer ... 6 more fields]
▶ grpsubgrp_df_cleaned: pyspark.sql.dataframe.DataFrame = [SubGrp_ID: string, Grp_Id: string]
▶ hospital_df_cleaned: pyspark.sql.dataframe.DataFrame = [Hospital_id: string, Hospital_name: string ... 3 more fields]
▶ subgroup_df_cleaned: pyspark.sql.dataframe.DataFrame = [SubGrp_id: string, SubGrp_Name: string ... 1 more field]
▶ subscriber_df_cleaned: pyspark.sql.dataframe.DataFrame = [sub_id: string, first_name: string ... 12 more fields]
▶ patient_records_df_cleaned: pyspark.sql.dataframe.DataFrame = [Patient_id: integer, Patient_name: string ... 6 more fields]

+-----+-----+-----+-----+-----+-----+-----+
|Claim_Or_Rejected|SUB_ID|claim_amount|claim_date|claim_id|claim_type|disease_name|patient_id|
+-----+-----+-----+-----+-----+-----+-----+
|          0|     0|        0|      0|      0|       0|         0|       0|
+-----+-----+-----+-----+-----+-----+-----+-----+

Number of duplicates dropped in claims_df: 0
+-----+-----+
|SubGrpID| Disease_ID|Disease_name|
+-----+-----+
|      0|        0|        0|
+-----+-----+

```

```
Number of duplicates dropped in disease_df: 0
+-----+
|Country|premium_written|zipcode|Grp_Id|Grp_Name|Grp_Type|city|year|
+-----+
|  0|        0|    0|    0|     0|      0|   0|  0|  0|
+-----+



Number of duplicates dropped in group_df: 0
+-----+
|SubGrp_ID|Grp_Id|
+-----+
|  0|  0|
+-----+



Number of duplicates dropped in grpsubgrp_df: 0
+-----+
|Hospital_id|Hospital_name|city|state|country|
+-----+
|  0|    0|  0|  0|  0|
+-----+



▶ [subgroup_ur_cleaned: pyspark.sql.dataframe.DataFrame = [SubGrp_Id: string, Subgrp_Name: string ... 1 more field]
▶ [subscriber_df_cleaned: pyspark.sql.dataframe.DataFrame = [sub_id: string, first_name: string ... 12 more fields]
▶ [patient_records_df_cleaned: pyspark.sql.dataframe.DataFrame = [Patient_id: integer, Patient_name: string ... 6 more fields]
+-----+
|SubGrp_id|SubGrp_Name|Monthly_Premium|
+-----+
|  0|      0|      0|
+-----+



Number of duplicates dropped in subgroup_df: 0
+-----+
|sub_id|first_name|last_name|Street|Birth_date|Gender|Phone|Country|City|Zip Code|Subgrp_id|Elig_ind|eff_date|term_date|
+-----+
|  0|      27|       0|     0|      0|    0|  3|    0|    0|     0|    2|     4|    0|    0|
+-----+



Number of duplicates dropped in subscriber_df: 0
+-----+
|Patient_id|Patient_name|patient_gender|patient_birth_date|patient_phone|disease_name|city|hospital_id|
+-----+
|  0|      17|       0|           0|          2|      0|    0|    0|
+-----+



Number of duplicates dropped in patient_records_df: 0
```

## Table: Patient Before Cleaning

187158	Harbir	Female	1924-06-30 +91 0112009318	Galactosemia	Rourkela	H1001
112766	Brahmdev	Female	1948-12-20 +91 1727749552	Bladder cancer	Tiruvottiyur	H1016
199252	Ujjawal	Male	1980-04-16 +91 8547451606	Kidney cancer	Berhampur	H1009
133424	Ballari	Female	1969-09-25 +91 0106026841	Suicide	Bihar Sharif	H1017
172579	Devnath	Female	1946-05-01 +91 1868774631	Food allergy	Bidhanagar	H1019
171320	Atasi	Male	1967-10-02 +91 9747336855	Whiplash	Amravati	H1013
107794	Manish	Male	1967-06-06 +91 4354294043	Sunbathing	Panvel	H1004
130339	Aakar	Female	1925-03-05 +91 2777633911	Drug consumption	Bihar Sharif	H1000
110377	Gurudas	Male	1945-05-06 +91 1232859381	Dengue	Kamarhati	H1001
149367	null	Male	1925-06-12 +91 1780763280	Head banging	Bangalore	H1013
156168	null	Male	1976-02-03 +91 5586075345	Fanconi anaemia	Rajkot	H1004
114241	null	Female	1955-01-22 +91 4146391938	Breast cancer	Ghaziabad	H1015
146382	Dharmadaas	Male	1964-04-29 +91 6345482027	Anthrax	Bhalswa Jahangir Pur	H1019
132748	Brahmvir	Male	1991-11-11 +91 7316972612	Cystic fibrosis	Ambala	H1018
167340	null	Female	1981-01-25 +91 2960004518	Galactosemia	Surendranagar Dud...	H1003
135184	Bhagvan	Female	1966-07-24 +91 0297693485	Dengue	Bhimavararam	H1018
179662	Amritkala	Female	1933-11-20 +91 0537157280	Smallpox	Meerut	H1018
184479	Bandhu	Male	1996-10-15 +91 0695289163	Pollen allergy	Chinsurah	H1010
156988	Bhagavaana	Female	1935-09-16 +91 6071745855	Breast cancer	Shahjahanpur	H1012
132870	null	Female	1924-11-09 +91 8906694405	Glaucoma	Jabalpur	H1017

## After Cleaning

02:37 PM (1s) 15

patient\_records\_df\_cleaned.show()

(2) Spark Jobs

132748  Brahmvir  Male  1991-11-11 +91 7316972612  Cystic fibrosis  Ambala  H1018
172579  Devnath  Female  1946-05-01 +91 1868774631  Food allergy  Bidhannagar  H1019
146382  Dharmadaas  Male  1964-04-29 +91 6345482027  Anthrax  Bhalswa Jahangir Pur  H1019
114241  NA  Female  1955-01-22 +91 4146391938  Breast cancer  Ghaziabad  H1015
148137  Umang  Female  1963-07-14 +91 9485838770  Pet allergy  Haridwar  H1002
171320  Atasi  Male  1967-10-02 +91 9747336855  Whiplash  Amravati  H1013
187158  Harbir  Female  1924-06-30 +91 0112009318  Galactosemia  Rourkela  H1001
199252  Ujjawal  Male  1980-04-16 +91 8547451606  Kidney cancer  Berhampur  H1009
149367  NA  Male  1925-06-12 +91 1780763280  Head banging  Bangalore  H1013
133424  Ballari  Female  1969-09-25 +91 0106026841  Suicide  Bihar Sharif  H1017
130339  Aakar  Female  1925-03-05 +91 2777633911  Drug consumption  Bihar Sharif  H1000
156988  Bhagavaana  Female  1935-09-16 +91 6071745855  Breast cancer  Shahjahanpur  H1012
112766  Brahmdev  Female  1948-12-20 +91 1727749552  Bladder cancer  Tiruvottiyur  H1016
107794  Manish  Male  1967-06-06 +91 4354294043  Sunbathing  Panvel  H1004
110377  Gurudas  Male  1945-05-06 +91 1232859381  Dengue  Kamarhati  H1001
132870  NA  Female  1924-11-09 +91 8906694405  Glaucoma  Jabalpur  H1017
179662  Amritkala  Female  1933-11-20 +91 0537157280  Smallpox  Meerut  H1018
184479  Bandhu  Male  1996-10-15 +91 0695289163  Pollen allergy  Chinsurah  H1010

only showing top 20 rows

**Table: Subscriber**  
Before Cleaning

02:24 PM (1s) 12 Python

subscriber\_df.show()

(1) Spark Jobs

9-09-25 1995-06-05
SUBID10004  Devnath  Srivastav  Magar Zila 1946-05-01 Female +91 1868774631  India  Bidhannagar  531742  S110  N 196
6-05-01 1970-12-09
SUBID10005  Atasi  Seth  Khatri Nagar 1967-10-02  Male +91 9747336855  India  Amravati  229062  S104  Y 198
7-10-02 1995-02-13
SUBID10006  Manish  Maurya Swaminathan Chowk 1967-06-06  Male +91 4354294043  India  Panvel  438733  S109  null 198
7-06-06 1995-03-21
SUBID10007  Aakar  Yadav  Swamy 1925-03-05 Female +91 2777633911  India  Bihar Sharif  535907  S104  N 194
5-03-05 1946-11-07
SUBID10008  Gurudas  Gupta  Sarin Nagar 1945-05-06  Male +91 1232859381  India  Kamarhati  933226  S103  Y 196
5-05-06 1970-09-16
SUBID10009  null  Gupta  Thakur Circle 1925-06-12  Male +91 1780763280  India  Bangalore  957469  S105  Y 194
5-06-12 1953-08-30
SUBID1010  null  Divedi  Dhillon 1976-02-03  Male +91 5586075345  India  Rajkot  911319  S102  Y 199
6-02-03 2002-01-27
SUBID10011  null Vishwakarma  Rajagopalan 1955-01-22 Female +91 4146391938  India  Ghaziabad  337042  S106  N 197
5-01-22 1978-11-02
SUBID10012 Dharmadaas  Tiwari  Rama 1964-04-29  Male +91 6345482027  India Bhalswa Jahangir Pur  430793  S103  N 198
4-04-29 1988-02-07
SUBID10013  Brahmdev  Rai  Shah Path 1991-11-11  Male +91 7316972612  India  Ambala  249898  S106  N 201
1-11-11 2020-05-23

## After Cleaning

4 minutes ago (1s) 13 Python

subscriber\_df\_cleaned.show();

(2) Spark Jobs

SUBID10013  Brahmvir  Rai  Shah Path 1991-11-11  Male +91 7316972612  India  Ambala  249898  S106  N 201
1-11-11 2020-05-23
SUBID10012 Dharmadaas  Tiwari  Rama 1964-04-29  Male +91 6345482027  India Bhalswa Jahangir Pur  430793  S103  N 198
4-04-29 1988-02-07
SUBID10011  NA Vishwakarma  Rajagopalan 1955-01-22 Female +91 4146391938  India  Ghaziabad  337042  S106  N 197
5-01-22 1978-11-02
SUBID10018 Bhagavaana  Kumar  Kulkarni Zila 1935-09-16 Female +91 6071745855  India  Shahjahanpur  597276  S101  N 195
5-09-16 1958-05-31
SUBID10002  Ujjawal  Devi  Mammen Zila 1980-04-16  Male +91 8547451606  India  Berhampur  914455  S106  N 200
0-04-16 2008-05-04
SUBID10009  NA  Gupta  Thakur Circle 1925-06-12  Male +91 1780763280  India  Bangalore  957469  S105  Y 194
5-06-12 1953-08-30
SUBID1020  Umang  Srivastav  Balay Chowk 1963-07-14 Female +91 9485838770  India  Haridwar  181692  S109  Y 198
3-07-14 1986-01-15
SUBID1010  NA  Divedi  Dhillon 1976-02-03  Male +91 5586075345  India  Rajkot  911319  S102  Y 199
6-02-03 2002-01-27
SUBID10000  Harbir Vishwakarma  Baria Marg 1924-06-30 Female +91 0112009318  India  Rourkela  767058  S107  Y 194
4-06-30 1954-01-14
SUBID10014  NAI  Srivastav  Chandra Pathi 1981-01-25 Female +91 2960004518  India Surendranagar Dard...  1119661  S102  N 200

## 9. Writing the cleaned data to AWS S3.

After cleaning and analysis, we now have high-quality, processed/cleaned data which is exported back to our AWS S3 bucket, creating a new 'cleaned-data' folder. This helps to ensure that we maintain a clear separation between raw and processed data, and provides a clean dataset for future use or additional analytics.

Environment: Databricks, PySpark, AWS S3

```
# WRITING DATA

# # Writing the cleaned data to AWS S3
claims_df_cleaned.write.option("header", "true").mode("overwrite").csv("s3a://health-insurance-capstone/clean-data/claims")
disease_df_cleaned.write.option("header", "true").mode("overwrite").csv("s3a://health-insurance-capstone/clean-data/disease")
group_df_cleaned.write.option("header", "true").mode("overwrite").csv("s3a://health-insurance-capstone/clean-data/group")
grpsubgrp_df_cleaned.write.option("header", "true").mode("overwrite").csv("s3a://health-insurance-capstone/clean-data/grpsubgrp")
hospital_df_cleaned.write.option("header", "true").mode("overwrite").csv("s3a://health-insurance-capstone/clean-data/hospital")
subgroup_df_cleaned.write.option("header", "true").mode("overwrite").csv("s3a://health-insurance-capstone/clean-data/subgroup")
subscriber_df_cleaned.write.option("header", "true").mode("overwrite").csv("s3a://health-insurance-capstone/clean-data/subscriber")
patient_records_df_cleaned.write.option("header", "true").mode("overwrite").csv("s3a://health-insurance-capstone/clean-data/patient")

# (14) Spark Jobs
Job 259 View (Stages: 1/1)
Job 260 View (Stages: 1/1)
Job 261 View (Stages: 1/1, 1 skipped)
Job 262 View (Stages: 1/1)
Job 263 View (Stages: 1/1, 1 skipped)
Job 264 View (Stages: 1/1)
Job 265 View (Stages: 1/1, 1 skipped)
Job 266 View (Stages: 1/1)
Job 267 View (Stages: 1/1, 1 skipped)
Job 268 View (Stages: 1/1)
Job 269 View (Stages: 1/1, 1 skipped)
Job 270 View (Stages: 1/1)
Job 271 View (Stages: 1/1, 1 skipped)
Job 272 View (Stages: 1/1)
```

Amazon S3

Buckets

Access Grants

Access Points

Object Lambda Access Points

Multi-Region Access Points

Batch Operations

IAM Access Analyzer for S3

Block Public Access settings for this account

▼ Storage Lens

Dashboards

Storage Lens groups

AWS Organizations settings

Feature spotlight: [?](#)

► AWS Marketplace for S3

Amazon S3 > Buckets > health-insurance-capstone > clean-data/

clean-data/

Objects (8) info

Copy S3 URI Copy URL Download Open Actions Create folder Upload

Find objects by prefix:

Name	Type	Last modified	Size	Storage class
claims/	Folder	-	-	-
disease/	Folder	-	-	-
group/	Folder	-	-	-
grpsubgrp/	Folder	-	-	-
hospital/	Folder	-	-	-
patient/	Folder	-	-	-
subgroup/	Folder	-	-	-
subscriber/	Folder	-	-	-

Amazon S3

Buckets

Access Grants

Access Points

Object Lambda Access Points

Multi-Region Access Points

Batch Operations

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▼ Storage Lens

Dashboards

Storage Lens groups

AWS Organizations settings

Feature spotlight: [?](#)

► AWS Marketplace for S3

Amazon S3 > Buckets > health-insurance-capstone > clean-data/ > claims/

claims/

Objects (6) info

Copy S3 URI Copy URL Download Open Actions Create folder Upload

Find objects by prefix:

Name	Type	Last modified	Size	Storage class
<a href="#">committed_2398982369505752359</a>	CSV	July 10, 2024, 18:35:32 (UTC-05:00)	113.0 B	Standard
<a href="#">committed_5229213239375621544</a>	CSV	July 10, 2024, 18:45:40 (UTC-05:00)	212.0 B	Standard
<a href="#">started_2398982369505752359</a>	CSV	July 10, 2024, 18:35:31 (UTC-05:00)	0 B	Standard
<a href="#">started_5229213239375621544</a>	CSV	July 10, 2024, 18:45:39 (UTC-05:00)	0 B	Standard
<a href="#">SUCCESS</a>	CSV	July 10, 2024, 18:45:40 (UTC-05:00)	0 B	Standard
<a href="#">part-00000</a>	CSV	July 10, 2024, 18:45:43 (UTC-05:00)	4.7 KB	Standard

## 10. Upload cleaned data corresponding to each data set into a redshift table.

For efficient querying and long-term storage, the cleaned data is loaded to S3 to AWS Redshift. Each dataset is loaded into its corresponding table in the Redshift cluster. Similarly, each use case output is stored in a separate Redshift table within a schema named **Project-Output**."

**Environment:** AWS Redshift, AWS S3

The screenshot shows the AWS Redshift Query Editor interface. A modal dialog titled "Load data" is open, prompting the user to "Choose archive in S3". The dialog lists objects from the "clean-data" folder in the "patient" table of the "health-insurance-capstone" bucket. One file, "part-00000-tid-885713106833c29492-b58107b0-1200-4a39-8282-13972739f3cd454-1-c000.csv", is selected and highlighted. Below the modal, the main query editor window shows the SQL command:

```
COPY dev."project-output".subscriber FROM 's3://health-insurance-capstone/clean-data/subscriber/part-00000-tid-7394783108079508452-931c445e-454b-4e22-b595-98c56289f285-452-1-c000'
```

The "Table options" section of the "Load data" dialog is visible, showing the "Load new table" option selected. The "Columns" section lists the columns of the CSV file: Patient\_Id, Patient\_name, patient\_gender, patient\_birth..., patient\_phone, disease\_name, city, and hospital\_id. The "Column options" section shows the "No default value" option selected for the "Patient\_Id" column.

Screenshot of the AWS Redshift Query Editor v2 showing a successful COPY operation.

The interface shows the following details:

- Serverless: healthcarewg** database.
- dev** schema.
- project-output** table.
- patient** table created successfully.
- Load data** dialog open, showing the table structure:

Column name	Data type	Encoding
Patient_id	INTEGER	No selection
Patient_name	VARCHAR	No selection
patient_gender	VARCHAR	No selection
patient_birth_date	DATE	No selection
patient_phone	VARCHAR	No selection
disease_name	VARCHAR	No selection
city	VARCHAR	No selection
hospital_id	VARCHAR	No selection

- Summary** section shows 0 rows returned.
- Info:** Load into table completed, 0 record(s) loaded successfully.
- Result set query:** `COPY dev."project-output".patient FROM 's3://health-insurance-capstone/clean-data/part-00000-tid-7394783189879588452-931c445e-454b-4e22-b595-9b56289f205-452-1-c000.csv'`

Screenshot of the AWS Redshift Query Editor v2 showing a successful COPY operation.

The interface shows the following details:

- Serverless: healthcarewg** database.
- dev** schema.
- project-output** table.
- patient** table created successfully.
- Load data** dialog open, showing the table structure:

Column name	Data type	Encoding
Patient_id	INTEGER	No selection
Patient_name	VARCHAR	No selection
patient_gender	VARCHAR	No selection
patient_birth_date	DATE	No selection
patient_phone	VARCHAR	No selection
disease_name	VARCHAR	No selection
city	VARCHAR	No selection
hospital_id	VARCHAR	No selection

- Summary** section shows 0 rows returned.
- Info:** Load into table 'patient' completed, 70 record(s) loaded successfully.
- Result set query:** `COPY dev."project-output".patient FROM 's3://health-insurance-capstone/clean-data/part-00000-tid-8857131068336239492-b58107b0-1200-4a39-8282-13972739f3cd-454-1-c000.csv' TAM_ROLE`

## 11. Use Cases

- **Disease Analysis:** Identify the disease with the maximum number of claims.

Here, insurance claims are grouped by disease name, count the occurrences, and identify the disease with the maximum claims. The resulting DataFrame is displayed and then saved as a permanent table in Databricks, allowing for persistent storage and future analysis.

```
# 1. Disease with maximum number of claim

from pyspark.sql.functions import col

# Group by disease_name and count the occurrences, then get the one with the maximum count
max_claims_disease_df = claims_df_cleaned.groupBy("disease_name") \
    .count() \
    .orderBy(col("count").desc()) \
    .limit(1)

# Display the result
max_claims_disease_df.show()

# Saving as a permanent table
permanent_table_name = "max_claims_disease"
max_claims_disease_df.write.mode("overwrite").saveAsTable(permanent_table_name)

# Saving data to AWS S3
max_claims_disease_df.write.option("header", "true").mode("overwrite").csv("s3a://health-insurance-capstone/use-case-output/max_claims_disease")

(15) Spark Jobs
▶ max_claims_disease_df: pyspark.sql.dataframe.DataFrame = [disease_name: string, count: long]
+-----+
|disease_name|count|
+-----+
| Pet allergy|   3|
+-----+
```

- **Subscriber Analysis:** Find subscribers under the age of 30 who subscribe to any subgroup.

This query joins subscriber and subgroup data, filters out subscribers under 30 years old, and selects all relevant subscriber columns

```
# 2. Subscribers under age 30 subscribing to any subgroup
from pyspark.sql.functions import datediff, current_date

subscribers_under_30_df = subscriber_df.join(subgroup_df, subscriber_df["Subgrp_id"] == subgroup_df["SubGrp_id"]) \
    .filter(datediff(current_date(), col("Birth_date")) / 365 < 30) \
    .select(subscriber_df["*"])

subscribers_under_30_df.show()

#Saving as a permanent table
permanent_table_name = "subscribers_under_30_df"
subscribers_under_30_df.write.format("csv").mode("overwrite").saveAsTable(permanent_table_name)
# Saving data to AWS S3
subscribers_under_30_df.write.option("header", "true").mode("overwrite").csv("s3a://health-insurance-capstone/use-case-output/subscribers_under_30")

▶ (4) Spark Jobs
▶ [subscribers_under_30_df: pyspark.sql.dataframe.DataFrame = [sub_id: string, first_name: string ... 12 more fields]
+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+
| sub_id | first_name | last_name | Street | Birth_date | Gender | Phone | Country | City | Zip Code | Subgrp_id | Elig_ind | eff_date | t
erm_date |
+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+
|SUBID10017| Bandhu | Seth | Varughese | 1996-10-15 | Male | +91 0695289163 | India | Chinsurah | 136713 | S108 | N | 2016-10-15 | 2018-06-08 |
|SUBID10083| Bhilangana | Pandit | Ramachandran Path | 1995-01-04 | Female | +91 6653069630 | India | Fatehpur | 359466 | S109 | Y | 2015-01-04 | 2017-10-05 |
|SUBID10093| Chandavarman | Singh | Sarkar Circle | 1997-05-10 | Others | +91 6559031791 | India | Navi Mumbai | 83240 | S110 | N | 2017-05-10 | 2022-08-27 |
+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+
```

- **Group Analysis:** Determine which group has the maximum number of subgroups.

This query groups data by Grp\_Id and counts the subgroups for each group. It then identifies the group with the most subgroups, displays the result, and saves this information as a permanent table in Databricks, ensuring the data is persistently stored for future analysis

```
# 3. Group with maximum subgroup
# Group by Grp_Id and count the subgroups, then get the one with the maximum count
max_subgroup_group_df = grp_subgrp_df.groupBy("Grp_Id") \
    .count() \
    .orderBy(col("count").desc()) \
    .limit(1)

# Display the result
max_subgroup_group_df.show()

# Saving as a permanent table
permanent_table_name = "max_subgroup_group"
max_subgroup_group_df.write.mode("overwrite").saveAsTable(permanent_table_name)
# Saving data to AWS S3
max_subgroup_group_df.write.option("header", "true").mode("overwrite").csv("s3a://health-insurance-capstone/use-case-output/max_subgroup_group")

▶ (13) Spark Jobs
▶ [max_subgroup_group_df: pyspark.sql.dataframe.DataFrame = [Grp_Id: string, count: long]
+-----+-----+
| Grp_Id | count |
+-----+-----+
| GRP104 | 2 |
+-----+-----+
```

- **Hospital Analysis:** Identify the hospital that serves the most number of patients.

This DataFrame groups the data by hospital\_id, counts the number of patients, and selects the hospital with the highest patient count.

```
from pyspark.sql.functions import col

# Group by hospital_id and count the patients, then get the hospital with the maximum count
most_patients_hospital_df = patient_records_df.groupBy("hospital_id") \
    .count() \
    .orderBy(col("count").desc()) \
    .limit(1)

# Display the result
most_patients_hospital_df.show()

# Saving as a permanent table
permanent_table_name = "most_patients_hospital"
most_patients_hospital_df.write.mode("overwrite").saveAsTable(permanent_table_name)
# Saving data to AWS S3
most_patients_hospital_df.write.option("header", "true").mode("overwrite").csv("s3a://health-insurance-capstone/use-case-output/most_patients_hospital")

▶ (13) Spark Jobs
▶ most_patients_hospital_df: pyspark.sql.dataframe.DataFrame = [hospital_id: string, count: long]
+-----+---+
|hospital_id|count|
+-----+---+
|      H1017|     9|
+-----+---+
```

- **Subgroup Analysis:** Find out which subgroup is subscribed to the most.

```
# 5. Subgroup subscribed most number of times
from pyspark.sql.functions import col

# Group by Subgrp_id and count the occurrences, then get the one with the maximum count
most_subscribed_subgroup_df = subscriber_df.groupBy("Subgrp_id") \
    .count() \
    .orderBy(col("count").desc()) \
    .limit(1)

# Display the result
most_subscribed_subgroup_df.show()

# Saving as a permanent table
permanent_table_name = "most_subscribed_subgroup"
most_subscribed_subgroup_df.write.mode("overwrite").saveAsTable(permanent_table_name)

# Saving data to AWS S3
most_subscribed_subgroup_df.write.option("header", "true").mode("overwrite").csv("s3a://health-insurance-capstone/use-case-output/most_subscribed_subgroup")

▶ (13) Spark Jobs
▶ most_subscribed_subgroup_df: pyspark.sql.dataframe.DataFrame = [Subgrp_id: string, count: long]
+-----+---+
|Subgrp_id|count|
+-----+---+
|      S104|    13|
+-----+---+
```

This DataFrame groups the data by Subgrp\_id, counts the subscriptions, and selects the subgroup with the highest subscription count.

- **Claims Rejection Analysis:** Calculate the total number of claims that were rejected.

The script filters claims\_df for rejected claims and counts them. To save this count as a permanent table, it converts the count into a DataFrame and saves it under total\_rejected\_claims.

```
# 6. Total number of claims which were rejected
from pyspark.sql import Row

total_rejected_claims = claims_df.filter(col("Claim_Or_Rejected") == "Rejected") \
    .count()
#print("Total number of rejected claims:", total_rejected_claims)
# Convert the count to a DataFrame
total_rejected_claims_df = spark.createDataFrame([Row(total_rejected_claims=total_rejected_claims)])

# Display the result
total_rejected_claims_df.show()

# Saving as a permanent table
permanent_table_name = "total_rejected_claims"
total_rejected_claims_df.write.mode("overwrite").saveAsTable(permanent_table_name)

# Saving data to AWS S3
total_rejected_claims_df.write.option("header", "true").mode("overwrite").csv("s3a://health-insurance-capstone/use-case-output/
total_rejected_claims")

(15) Spark Jobs
▶ total_rejected_claims_df: pyspark.sql.dataframe.DataFrame = [total_rejected_claims: long]
-----+
total_rejected_claims|
-----+
  0|
-----+
```

- **Claims Origin Analysis:** Determine the city from which most claims are coming.

This script joins claims\_df with subscriber\_df based on SUB\_ID and sub\_id to include city information. Then it Groups by city, counts claims, orders by count in descending order, and retrieves the city with the most claims.

```

# 7. Join claims_df with subscriber_df to get city information for claims
from pyspark.sql.functions import count, avg, year, current_date, desc
claims_with_city_df = claims_df.join(subscriber_df, claims_df.SUB_ID == subscriber_df["sub_id"], "left")

# City with most claims
city_most_claims = claims_with_city_df.groupBy("City").count().orderBy(desc("count")).first()
print(f"City with most claims: {city_most_claims['City']}")

# Convert to DataFrame
city_most_claims_df = spark.createDataFrame([city_most_claims])

# Display the result
city_most_claims_df.show()

#Saving as a permanent table
permanent_table_name = "city_most_claims"
city_most_claims_df.write.format("csv").mode("overwrite").saveAsTable(permanent_table_name)

# Saving data to AWS S3
city_most_claims_df.write.option("header", "true").mode("overwrite").csv("s3a://health-insurance-capstone/use-case-output/city_most_claims")

```

▶ (7) Spark Jobs

```

▶ [claims_with_city_df: pyspark.sql.dataframe.DataFrame = [Claim_Or_Rejected: string, SUB_ID: string ... 20 more fields]
▶ [city_most_claims_df: pyspark.sql.dataframe.DataFrame = [City: string, count: long]

City with most claims: Mysore
+-----+
| City|count|
+-----+
|Mysore|     2|
+-----+

```

- **Policy Type Analysis:** Identify whether subscribers mostly subscribe to government or private policies.

This script Groups subscriber\_df by Elig\_ind (government or private policy indicator) and counts the number of subscriptions for each and displays the table of government and private policy subscriptions sorted by count.

```

# 8. Government or private policy subscriptions
policy_type_subscription = subscriber_df.groupBy("Elig_ind").count().orderBy(desc("count"))
policy_type_subscription.show()

#Saving as a permanent table
permanent_table_name = "policy_type_subscription"
policy_type_subscription.write.format("csv").mode("overwrite").saveAsTable(permanent_table_name)

# Saving data to AWS S3
policy_type_subscription.write.option("header", "true").mode("overwrite").csv("s3a://health-insurance-capstone/use-case-output/policy_type_subscription")

```

▶ (6) Spark Jobs

```

▶ [policy_type_subscription: pyspark.sql.dataframe.DataFrame = [Elig_ind: string, count: long]

+-----+
|Elig_ind|count|
+-----+
| N|    50|
| Y|    46|
| null|     4|
+-----+

```

- **Premium Analysis:** Calculate the average monthly premium paid by subscribers to the insurance company.

This script uses subgroup\_df to calculate the average monthly premium paid by subscribers using avg("Monthly\_Premium")

```

# 9. Average monthly premium paid by subscribers
avg_monthly_premium = subgroup_df.select(avg("Monthly_Premium")).first()
print(f"Average monthly premium paid by subscribers: {avg_monthly_premium['avg(Monthly_Premium)']}")

# Convert to DataFrame
avg_monthly_premium_df = spark.createDataFrame([avg_monthly_premium])

# Display the result
avg_monthly_premium_df.show()

#Saving as a permanent table
permanent_table_name = "avg_monthly_premium"
avg_monthly_premium_df.write.format("csv").mode("overwrite").saveAsTable(permanent_table_name)

# Saving data to AWS S3
avg_monthly_premium_df.write.option("header", "true").mode("overwrite").csv("s3a://health-insurance-capstone/use-case-output/
avg_monthly_premium")

▶ (6) Spark Jobs
▶ avg_monthly_premium_df: pyspark.sql.dataframe.DataFrame = [avg(Monthly_Premium): double]
Average monthly premium paid by subscribers: 1870.0
+-----+
|avg(Monthly_Premium)|
+-----+
|          1870.0|
+-----+

```

- **Profitability Analysis:** Find out which group is most profitable.

This script calculates the total premium written for each group in group\_df, identifies the group with the highest total premium, and prints its Grp\_Id. It uses aggregation functions like sum() and orderBy() to determine and display the most profitable group based on premium contributions.

```

# 10. Most profitable group

most_profitable_group = group_df.groupBy("Grp_Id") \
    .agg(sum("premium_written").alias("total_premium")) \
    .orderBy(col("total_premium").desc()) \
    .first()

print("Most profitable group:", most_profitable_group["Grp_Id"])

# Convert to DataFrame
most_profitable_group_df = spark.createDataFrame([most_profitable_group])

# Display the result
most_profitable_group_df.show()

#Saving as a permanent table
permanent_table_name = "most_profitable_group"
most_profitable_group_df.write.format("csv").mode("overwrite").saveAsTable(permanent_table_name)

# Saving data to AWS S3
most_profitable_group_df.write.option("header", "true").mode("overwrite").csv("s3a://health-insurance-capstone/use-case-output/
most_profitable_group")

▶ (6) Spark Jobs
▶ most_profitable_group_df: pyspark.sql.dataframe.DataFrame = [Grp_Id: string, total_premium: long]
Most profitable group: GRP131
+-----+
|Grp_Id|total_premium|
+-----+
|GRP131|      99000|
+-----+

```

- **Pediatric Cancer Patients:** List all patients below age 18 who are admitted for cancer.

This script uses filter() on patient\_records\_df to select records where disease\_name contains "cancer" and the patient's age is below 18 and it shows patients below 18 admitted for cancer.

```
# 11. Patients below age of 18 admitted for cancer
from pyspark.sql.functions import sum as spark_sum

# Filter patients below 18 with cancer
patients_below_18_cancer = patient_records_df.filter(
    (col("disease_name").contains("cancer")) &
    (datediff(current_date(), col("patient_birth_date")) / 365 < 18)
)

# Display the result
patients_below_18_cancer.show()

#Saving as a permanent table
permanent_table_name = "patients_below_18_cancer"
patients_below_18_cancer.write.format("csv").mode("overwrite").saveAsTable(permanent_table_name)

# Saving data to AWS S3
patients_below_18_cancer.write.option("header", "true").mode("overwrite").csv("s3a://health-insurance-capstone/use-case-output/
patients_below_18_cancer")

▶ (2) Spark Jobs
▶ patients_below_18_cancer: pyspark.sql.dataframe.DataFrame = [Patient_id: integer, Patient_name: string ... 6 more fields]
+-----+-----+-----+-----+-----+-----+
|Patient_id|Patient_name|patient_gender|patient_birth_date|patient_phone|disease_name|city|hospital_id|
+-----+-----+-----+-----+-----+-----+
```

- **High-Value Cashless Insurance Patients:** List patients who have cashless insurance and total charges greater than or equal to Rs. 50,000.

This script performs a join between patient\_records\_df\_cleaned and claims\_df\_cleaned based on Patient\_id then filters the joined DataFrame to include only records where claim\_type is "claims of value" and claim\_amount is 50,000 or more. Finally, selects the necessary columns from both DataFrames (patient\_records\_df\_cleaned and claims\_df\_cleaned) to include in the patients\_cashless DataFrame.

```

#12 List patients who have cashless insurance and have total charges greater than or equal for Rs. 50,000.
# Joining patients and claims DataFrames
joined_df = patient_records_df_cleaned.join(claims_df_cleaned, patient_records_df_cleaned["Patient_id"] == claims_df_cleaned["patient_id"])
# Applying filters
filtered_df = joined_df.filter(
    (claims_df_cleaned["claim_type"] == "claims of value") &
    (claims_df_cleaned["claim_amount"].cast("int") >= 50000)
)
# Selecting required columns
patients_cashless = filtered_df.select(
    patient_records_df_cleaned["Patient_id"],
    patient_records_df_cleaned["Patient_name"],
    patient_records_df_cleaned["hospital_id"],
    claims_df_cleaned["claim_amount"],
    claims_df_cleaned["claim_type"]
)
# Showing the result
patients_cashless.show()
# Saving as a permanent table
permanent_table_name = "patients_cashless"
patients_cashless.write.format("csv").mode("overwrite").saveAsTable(permanent_table_name)

# Saving data to AWS S3
patients_cashless.write.option("header", "true").mode("overwrite").csv("s3a://health-insurance-capstone/use-case-output/patients_cashless")

```

(8) Spark Jobs

- ▶ joined\_df: pyspark.sql.dataframe.DataFrame = [Patient\_id: integer, Patient\_name: string ... 14 more fields]
- ▶ filtered\_df: pyspark.sql.dataframe.DataFrame = [Patient\_id: integer, Patient\_name: string ... 14 more fields]
- ▶ patients\_cashless: pyspark.sql.dataframe.DataFrame = [Patient\_id: integer, Patient\_name: string ... 3 more fields]

Patient_id	Patient_name	Hospital_id	Claim_Amount	Claim_Type
189996	Ekant	H1003	192381	claims of value
109251	Anjushree	H1001	116937	claims of value
167340	NA	H1003	118628	claims of value
132947	Saroj	H1016	186502	claims of value
172579	Devnath	H1019	168634	claims of value
109342	Chitraranjan	H1011	125727	claims of value
1463821	Dharmadaas	H1019	75983	claims of value

- **Female Knee Surgery Patients:** List female patients over the age of 40 that have undergone knee surgery in the past year.

The script filters female patients over 40 years old from cleaned patient records (patient\_records\_df\_cleaned). It further refines this group to include only those who underwent knee surgery, displaying the results and saving them as a permanent CSV table named "knee\_surgery\_patients" in Spark.

Just now (2s) 30

```
# 13. Female patients over age 40 who underwent knee surgery in the past year
from pyspark.sql.functions import col, year, datediff, current_date

# Filter for female patients over the age of 40
female_patients_over_40 = patient_records_df.filter(
    (col("patient_gender") == "Female") &
    (datediff(current_date(), col("patient_birth_date")) / 365 > 40)
)
#female_patients_over_40.show()
# Filter for knee surgery in the past year
knee_surgery_patients = female_patients_over_40.filter(
    col("disease_name").contains("Knee Surgery"))

# Show the results
knee_surgery_patients.show()

# #Saving as a permanent table
permanent_table_name = "knee_surgery_patients"
knee_surgery_patients.write.format("csv").mode("overwrite").saveAsTable(permanent_table_name)

▶ (2) Spark Jobs
▶ female_patients_over_40: pyspark.sql.dataframe.DataFrame = [Patient_id: integer, Patient_name: string ... 6 more fields]
▶ knee_surgery_patients: pyspark.sql.dataframe.DataFrame = [Patient_id: integer, Patient_name: string ... 6 more fields]
+-----+-----+-----+-----+-----+-----+
|Patient_id|Patient_name|patient_gender|patient_birth_date|patient_phone|disease_name|city|hospital_id|
+-----+-----+-----+-----+-----+-----+
+-----+-----+-----+-----+-----+-----+
```

## 12. Result Creation on Redshift

The screenshot shows the AWS S3 console interface. On the left, there's a navigation sidebar with links like 'Amazon S3', 'Buckets', 'Access Grants', 'Access Points', etc. The main area shows a list of objects in a folder named 'use-case-output/'. The list includes 12 items, all of which are folders. The columns in the table are 'Name', 'Type', 'Last modified', 'Size', and 'Storage class'. The 'Actions' menu is visible at the top of the list.

Name	Type	Last modified	Size	Storage class
avg_monthly_premium/_	Folder	-	-	-
city_most_claims/_	Folder	-	-	-
knee_surgery_patients/_	Folder	-	-	-
max_claims_disease/_	Folder	-	-	-
max_subgroup_group/_	Folder	-	-	-
most_profitable_group/_	Folder	-	-	-
most_subscribed_subgroup/_	Folder	-	-	-
patients_below_18_cancer/_	Folder	-	-	-
patients_cashless/_	Folder	-	-	-
policy_type_subscription/_	Folder	-	-	-
subscribers_under_30/_	Folder	-	-	-
total_rejected_claims/_	Folder	-	-	-

**Redshift query editor v2**

Editor    Create    Load data    Run    Limit 100    Explain    Isolated session    Serverless: he...    dev    Schedule    ...

Filter resources: Serverless: healthcarewg  
 > awssdatacatalog  
 > dev  
 > project-output  
 > Tables    12  
 avg\_monthly\_premium  
 city\_most\_claims  
 knee\_surgery\_patients  
 max\_claims\_disease  
 max\_subgroup\_group  
 most\_profitable\_group  
 most\_subscribed\_subgroup  
 patients\_below\_18\_cancer  
 patients\_cashless  
 policy\_type\_subscription  
**subscribers\_under\_30**  
 total\_rejected\_claims  
 > Views    0

**Result 1 (3)**

sub_id	first_name	last_name	street	birth_date	gender	phone
SUBID10017	Bandhu	Seth	Varughese	1996-10-15	Male	+91 08952891
SUBID10083	Bhilangana	Pandit	Ramachandran Path	1995-01-04	Female	+91 65530666
SUBID10093	Chandavarman	Singh	Sarkar Circle	1997-05-10	Others	+91 65590317

Row 1, Col 52, Chr 52    Export    Chart    ⚙️

Query ID 3925    Elapsed time: 15 ms    Total rows: 3

**databricks**

**New**

- Workspace
- Recents
- Search
- Catalog**
- Workflows
- Compute
- Machine Learning
- Experiments

**Data**

Create Table    ×    ⚙️

Databases    ✓    ▾

Filter Databases

default

Tables

Filter Tables

- avg\_montshly\_premium
- city\_mosts\_claims
- knee\_surgresy\_patients
- max\_claims\_disease
- max\_claims\_disease
- max\_subgraoup\_group
- mosst\_profitable\_group
- mosst\_subscribed\_subgroup
- patiesnts\_below\_18\_cancer
- patiesnts\_cashless
- policy\_type\_susbscription
- subsscribers\_under\_30\_df
- total\_rejected\_claims