# *INTERIM PROJECT*

**Topic: Streaming ETL: Perform Extract-Transform-Load (ETL) operations on streaming data, transforming it into a more structured format or loading it into a database.**


**Submitted by**

**Sanjeev M**

**EMP ID: 2320436**

# Abstract:

Streaming Extract-Transform-Load (ETL) operations have become essential in modern data processing pipelines, especially with the rise of real-time data analytics and decision-making. This paper explores the concept of Streaming ETL, which involves extracting data from continuous streams, transforming it on-the-fly, and loading it into a structured format or database for further analysis. The primary objective of Streaming ETL is to handle high-volume, high-velocity data streams efficiently, ensuring timely and accurate data processing.

The abstract further delves into the key components and challenges of Streaming ETL. It discusses the importance of stream processing frameworks like Apache Kafka, Apache Flink, and Apache Storm for handling streaming data ingestion and processing. Additionally, it highlights the significance of scalable data transformation techniques, such as stream-based transformations using Apache Beam or Spark Streaming, to handle complex data manipulations in real-time.

Furthermore, the abstract touches upon the role of destination systems such as relational databases, data warehouses, or data lakes in storing and organizing the transformed data for downstream applications. It emphasizes the need for robust error handling, data quality checks, and monitoring mechanisms in Streaming ETL workflows to ensure data integrity and reliability.

# Introduction:

In today's data-driven world, the ability to process data in both real-time and batch modes is crucial for organizations aiming to extract valuable insights and make informed decisions. Streaming Extract-Transform-Load (ETL) and batch ETL are two essential methodologies that enable organizations to process data continuously as it flows in real-time or in larger, periodic batches. These methodologies involve extracting raw data, transforming it to a more structured format, and loading it into a database or data warehouse for further analysis.

**Table of Contents**

# Overview:

## Streaming ETL (Real-Time):

Real-time data ingestion using Apache Kafka from sensors and IoT devices in stores capturing sales data.
Apache Spark Streaming is used for real-time data processing and transformations on the streaming data.
Transformations include enrichment, aggregation, fraud detection, and inventory management as described earlier.
Enriched and transformed data is loaded into a data warehouse or data lake in near real-time for immediate analysis and reporting.

## Batch ETL (Near Real-Time):

In addition to real-time processing, the retail company also performs batch ETL processes at regular intervals (e.g., daily, hourly) to handle historical data and larger volumes.
Batch ETL jobs are scheduled using Apache Airflow or similar workflow management tools to process data in batches.
The batch ETL pipeline includes similar transformations as the real-time pipeline but operates on larger datasets and historical data.
Processed batch data is also loaded into the data warehouse or data lake, merging seamlessly with the real-time data for comprehensive analytics.

# Real-Time Streaming ETL

Real-time customer segmentation based on current purchases and behaviours.
Instantaneous fraud detection and prevention for immediate action.
Dynamic pricing adjustments based on real-time market demand signals.
Live inventory management and restocking notifications for store managers.
Batch ETL:

Historical trend analysis to identify seasonal patterns and long-term customer trends.
Large-scale data aggregation for quarterly and annual business reviews.
Regulatory compliance reporting requiring historical data analysis.
Data archiving and backup for long-term data retention and disaster recovery.

Streaming ETL involves processing data in near real-time as it is generated, enabling organizations to derive insights and respond to events promptly. On the other hand, batch ETL processes data in larger volumes and at scheduled intervals, allowing for deeper analysis of historical data and trend identification. Both methodologies play complementary roles in modern data architectures, addressing different use cases and requirements.

# Key Components:

1. Data Ingestion: Both streaming and batch ETL begin with data ingestion, where raw data is collected from various sources such as sensors, applications, databases, and external APIs. Streaming ETL uses technologies like Apache Kafka, Amazon Kinesis, or Azure Event Hubs to ingest and buffer real-time data streams. Batch ETL typically involves bulk data extraction from databases, files, or data lakes at predefined intervals.

2. Transformation: After data ingestion, the raw data undergoes transformations to clean, enrich, aggregate, and structure it for analysis. Streaming ETL employs stream processing frameworks like Apache Flink, Apache Spark Streaming, or Apache Storm to perform transformations on-the-fly as data arrives. Batch ETL uses batch processing frameworks like Apache Spark, Apache Hadoop, or Apache Beam to process data in larger chunks and perform complex transformations.

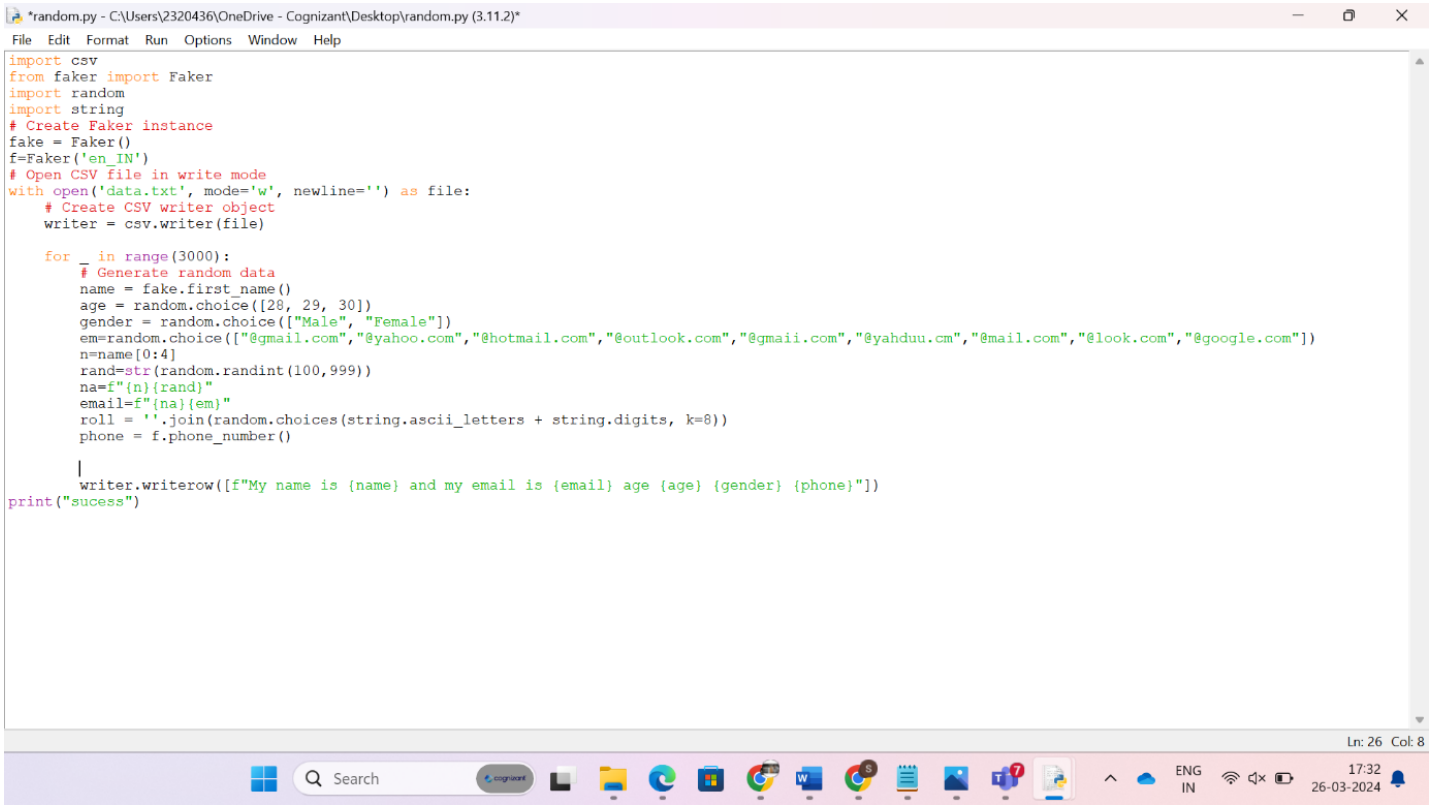
3. Loading: The transformed data is then loaded into a destination system such as a relational database, data warehouse, or data lake for storage and analysis. Both streaming and batch ETL pipelines integrate seamlessly with various storage and

processing systems, ensuring that the transformed data is available for downstream analytics, reporting, and application integration.

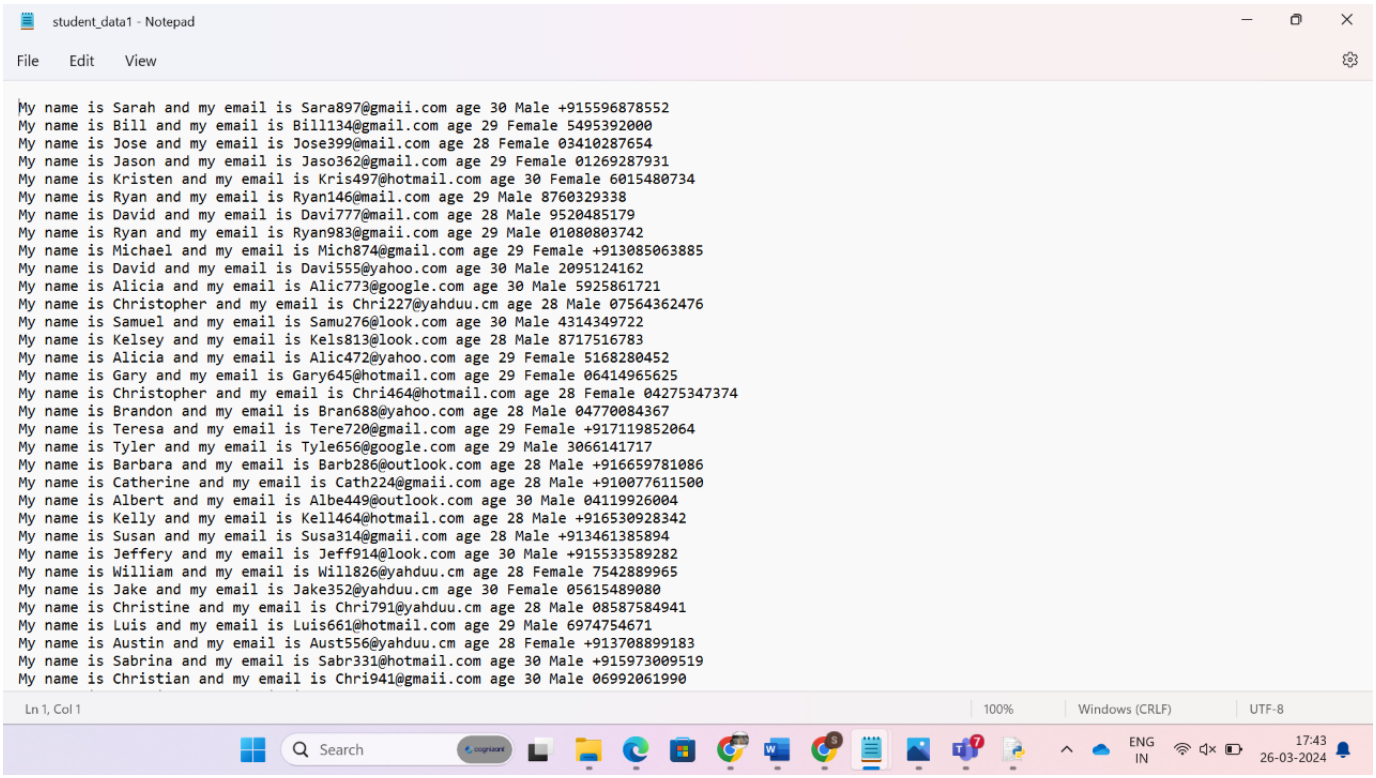
# CHAPTER 1- Data Ingestion

Data ingestion is the process of importing data from various sources into the system for analysis. In this project, the Unstructured dataset is ingested into the system using Apache Spark, specifically PySpark, which is a powerful data processing framework. PySpark provides functionality to read data from various sources, including CSV files, databases, and distributed storage systems.

For this project, using Python, I generated the student dataset is generated and stored in a CSV file, and PySpark's DataFrame API is used to read the data from this file into a DataFrame for further analysis.



Here input file is in unstructured format. Our goal is unstructured to structured format using spark. In both batch processing and stream processing we are going to do.

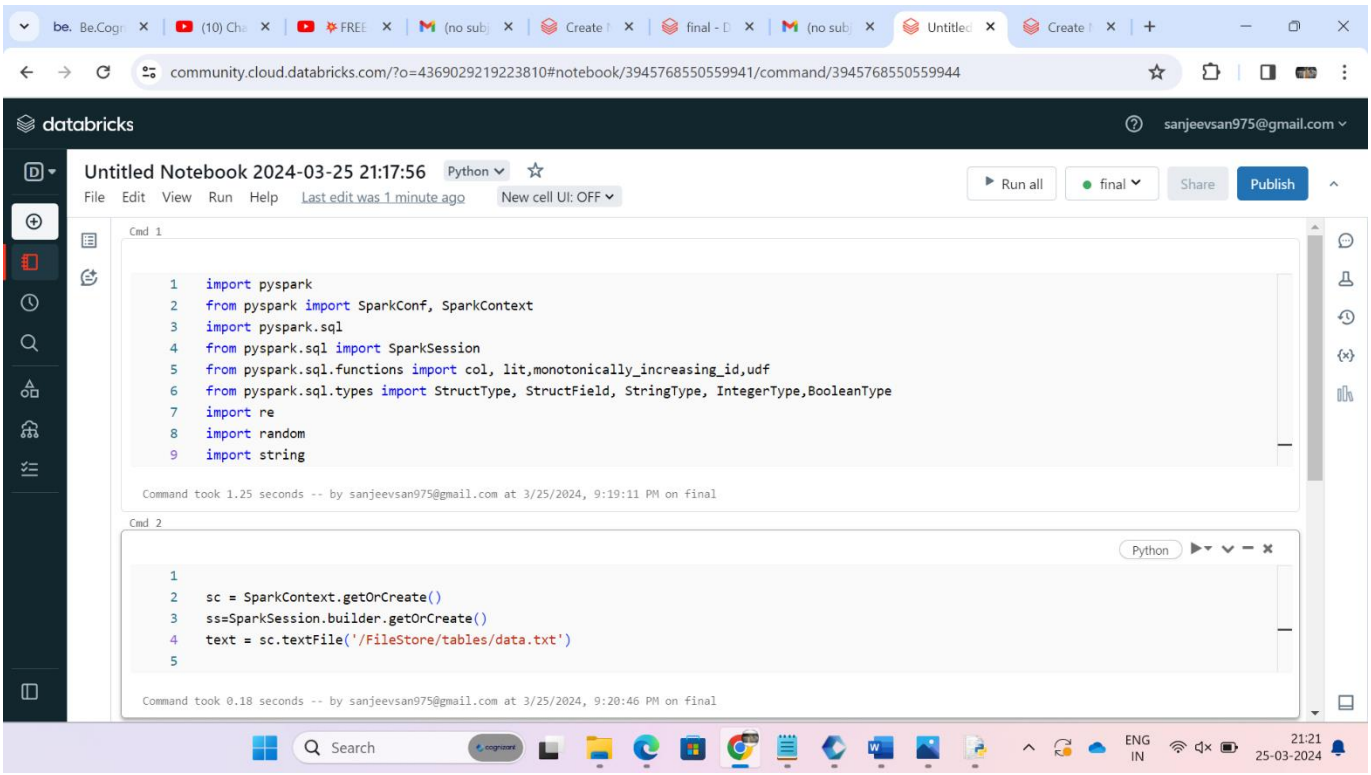


# Chapter 2

# BATCH STREAMING USING ETL:

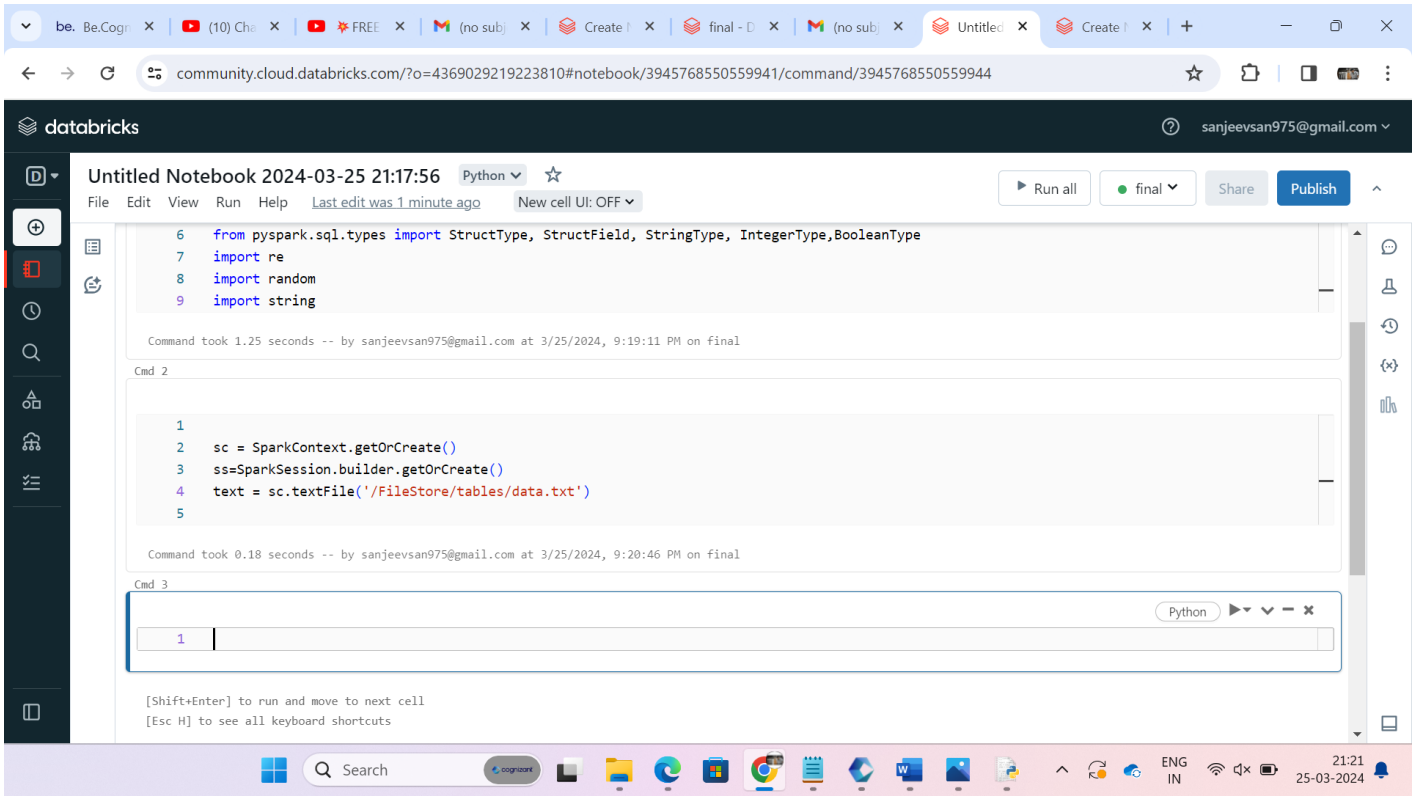
## Importing Libraries:

The code imports necessary libraries for working with Spark, including `pyspark`, `SparkConf`, `SparkContext`, `SparkSession`, and various functions and types from `pyspark.sql`.



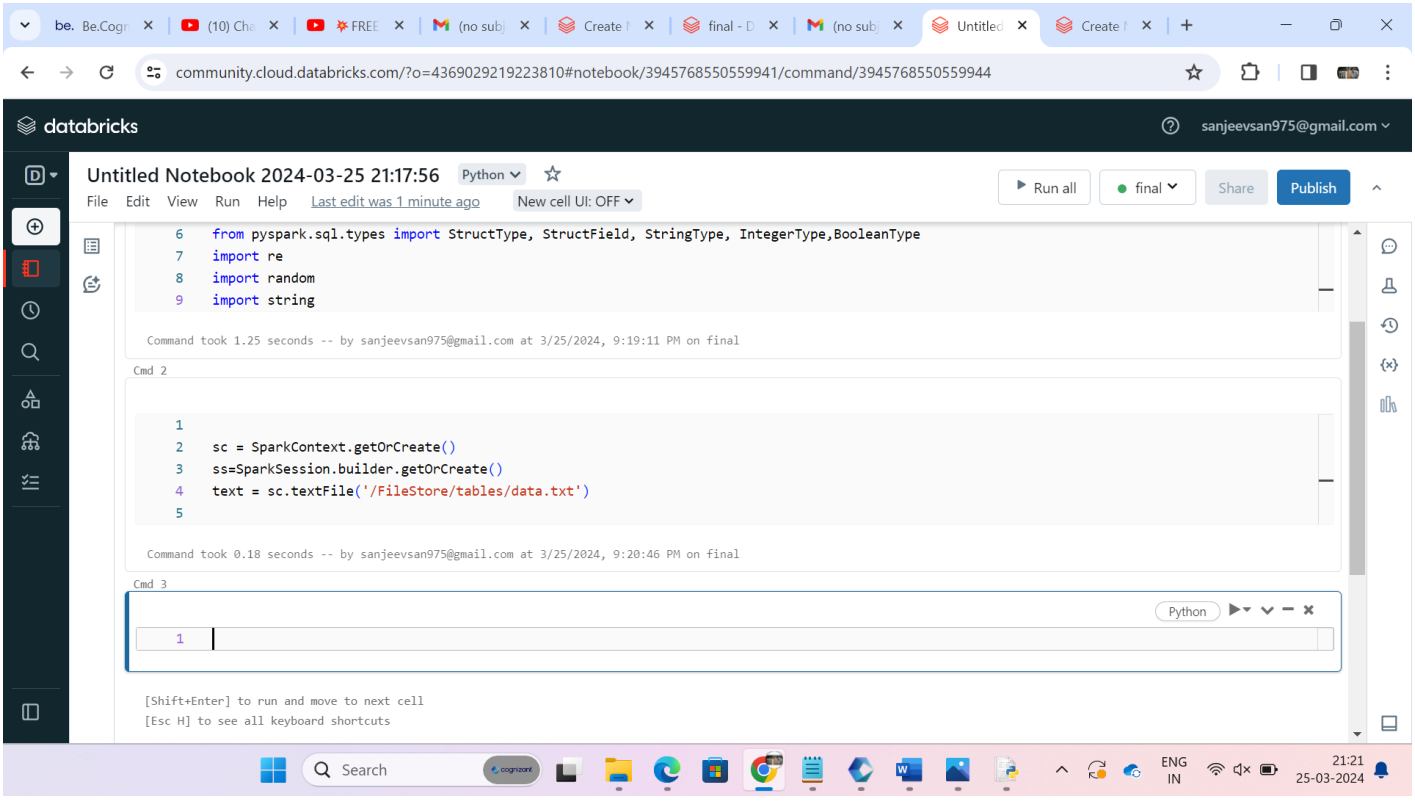
# Spark Context and Session Creation:

It creates a Spark Context (`sc`) and Spark Session (`ss`) to interact with Spark functionalities.



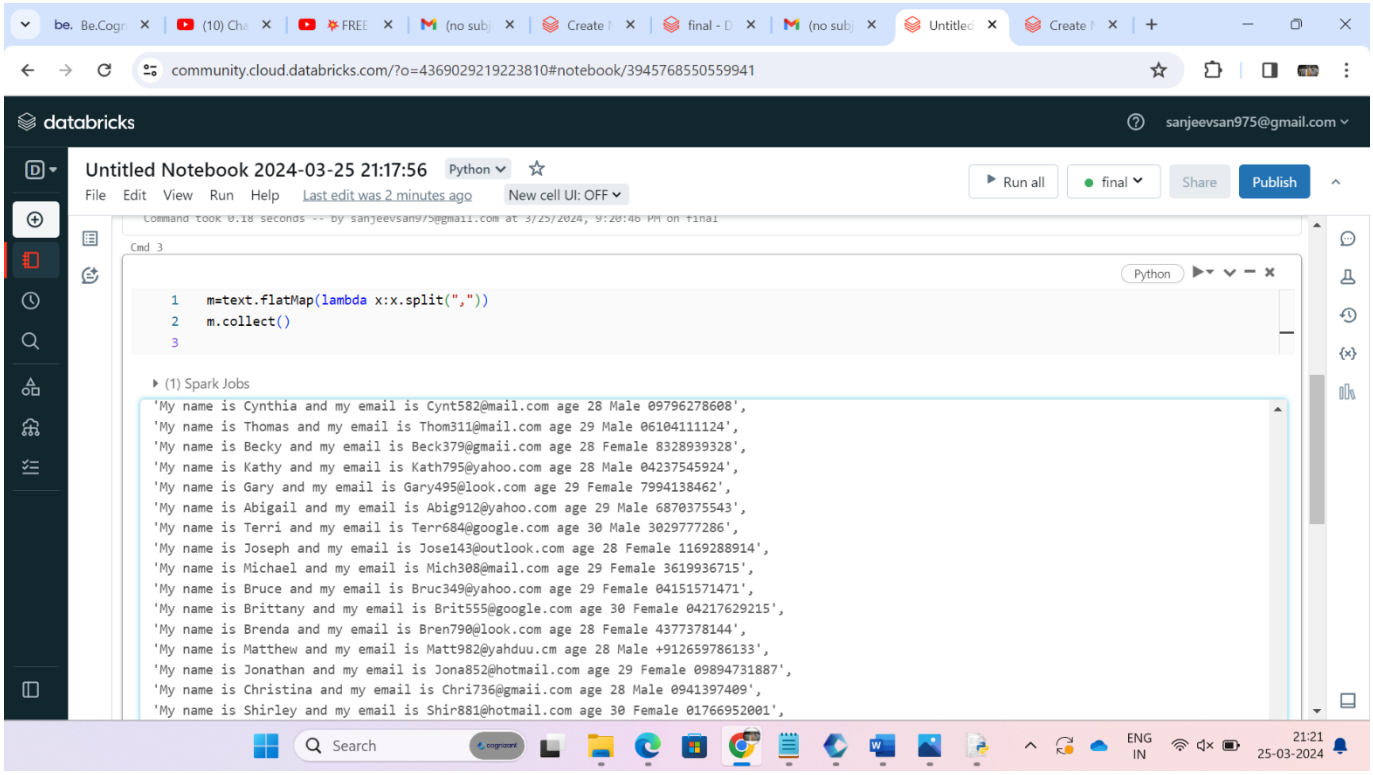
# Reading Text File:

The code reads the content of a text file named `dupli.txt` located in the `/FileStore/tables/` directory using Spark's `textFile` function. This file likely contains comma-separated values (CSV).



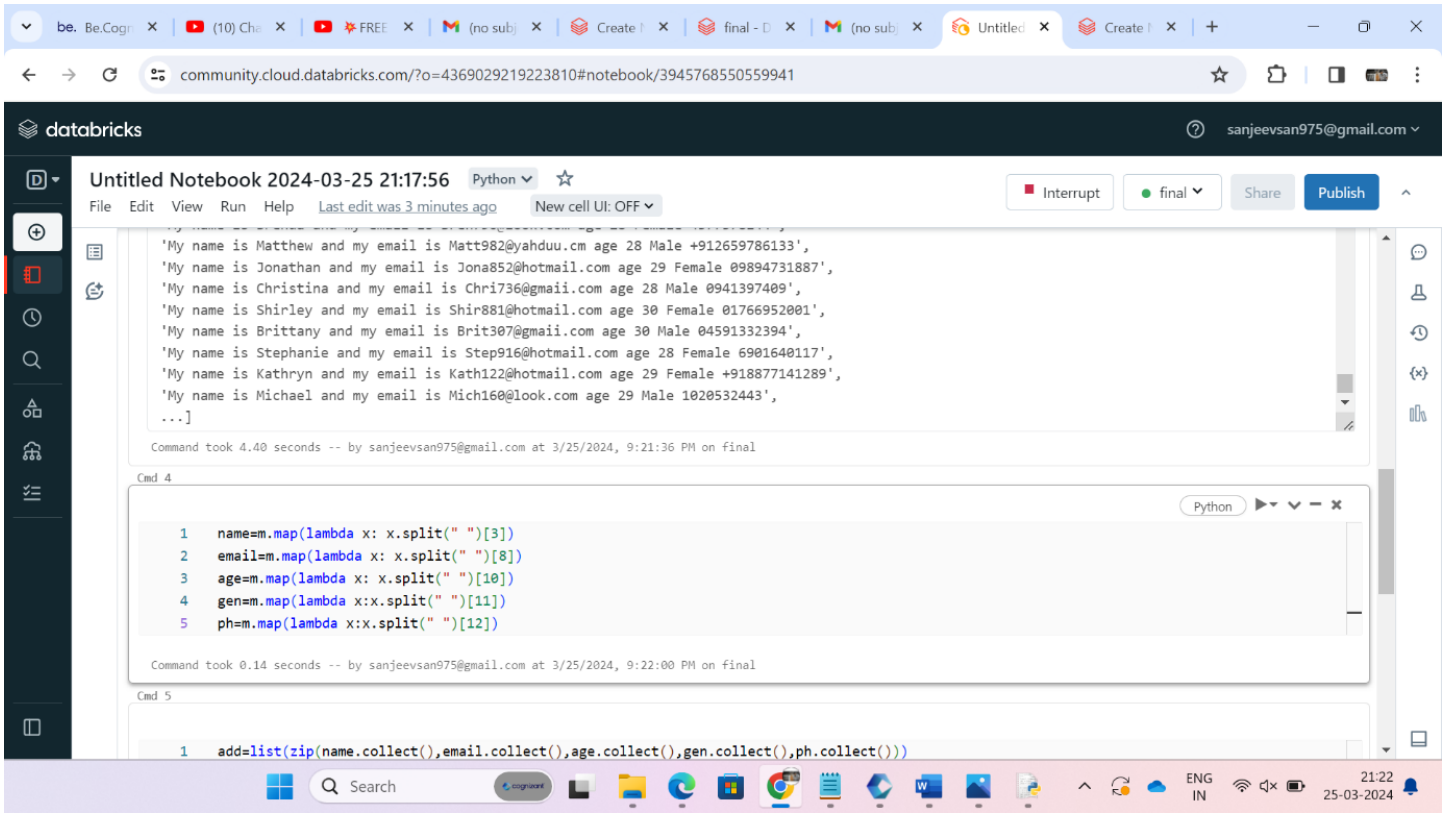
# FlatMapping and Splitting:

The `flatMap` operation is applied to split each line of the text file by comma delimiter, resulting in a flattened RDD of individual data elements.



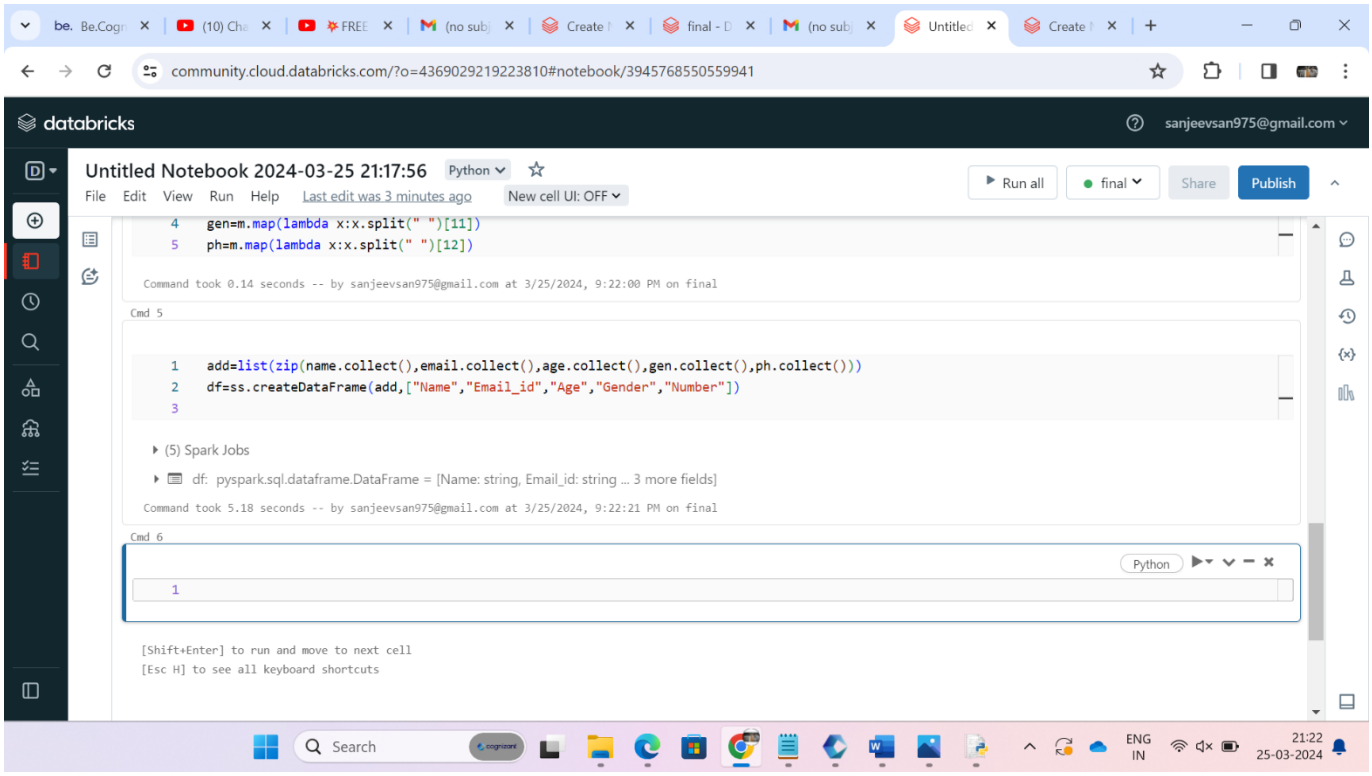
# Data Extraction:

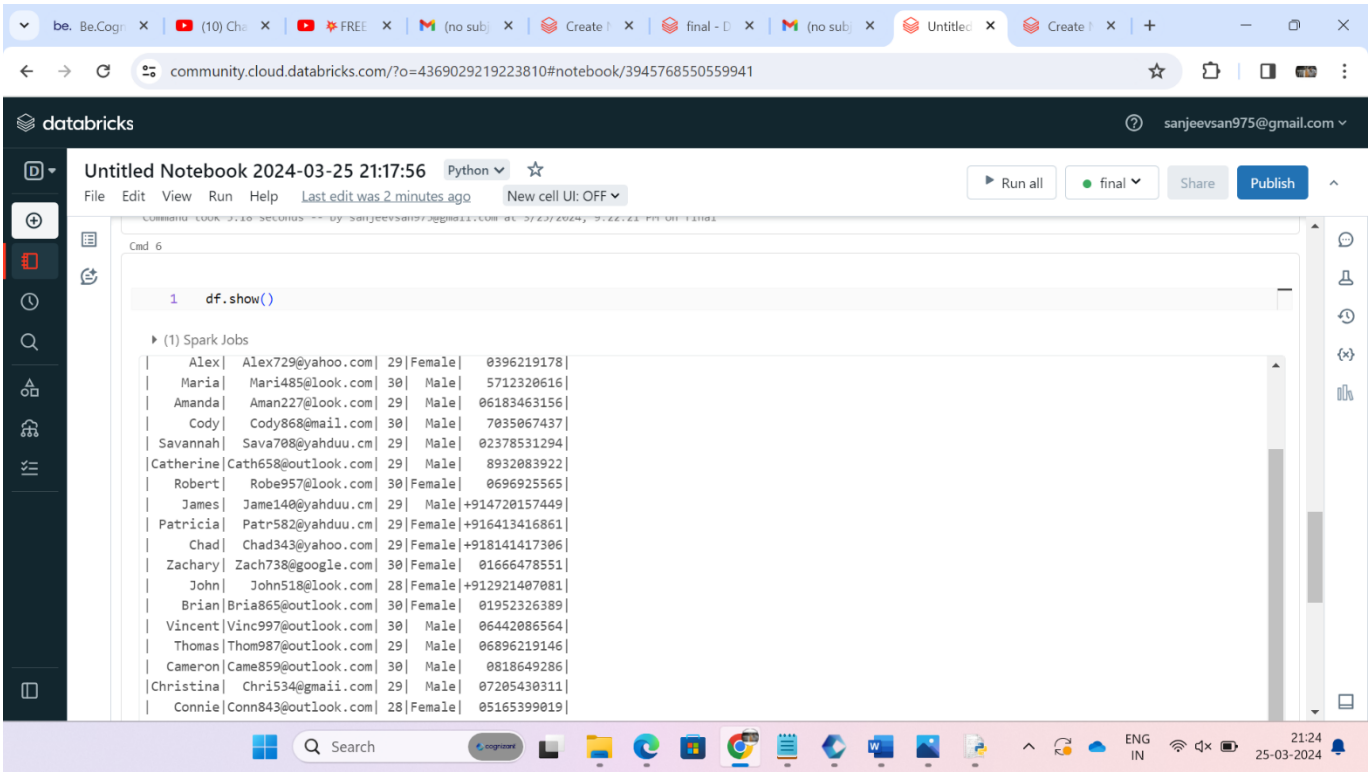
Lambda functions are used to extract specific fields like name, email, age, gender, and phone number from the flattened RDD.



# Creating DataFrame:

The extracted data is used to create a DataFrame named `df` with appropriate column names.

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1 df.show()
(1) Spark Jobs
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| Maria| Mari485@look.com| 30| Male| 5712320616|
| Amanda| Aman227@look.com| 29| Male| 06183463156|
| Cody| Cody868@mail.com| 30| Male| 7035067437|
| Savannah| Sava708@yahduu.cm| 29| Male| 02378531294|
|Catherine|Cath658@outlook.com| 29| Male| 8932083922|
| Robert| Robe957@look.com| 30|Female| 0696925565|
| James| Jame140@yahduu.cm| 29| Male|+914720157449|
| Patricia| Patr582@yahduu.cm| 29|Female|+916413416861|
| Chad| Chad343@yahoo.com| 29|Female|+918141417306|
| Zachary| Zach738@google.com| 30|Female| 01666478551|
| John| John518@look.com| 28|Female|+912921407081|
| Brian|Bria865@outlook.com| 30|Female| 01952326389|
| Vincent|Vinc997@outlook.com| 30| Male| 06442086564|
| Thomas|Thom987@outlook.com| 29| Male| 06896219146|
| Cameron|Came859@outlook.com| 30| Male| 0818649286|
|Christina| Chri534@gmaii.com| 29| Male| 07205430311|
| Connie|Conn843@outlook.com| 28|Female| 05165399019|
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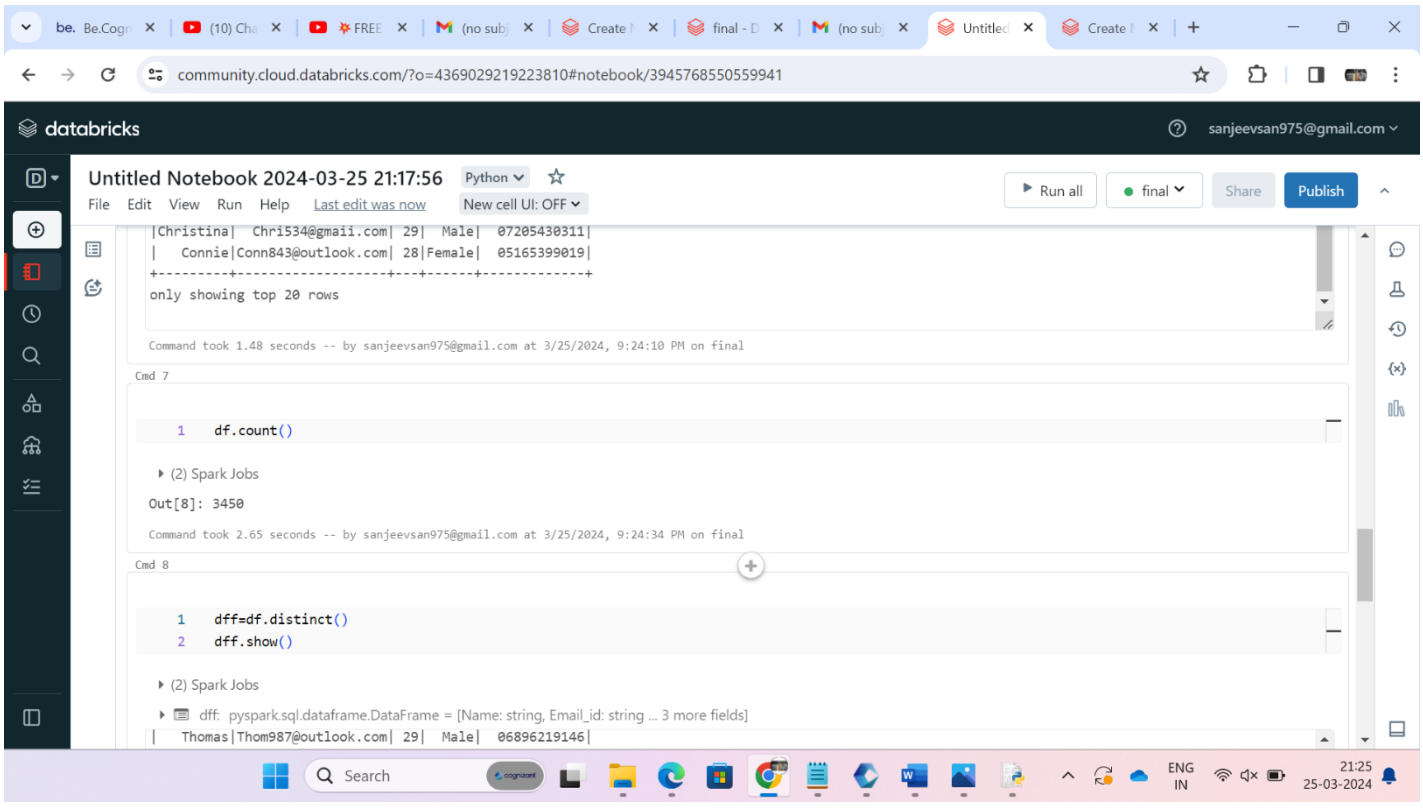
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| Connie|Conn843@outlook.com| 28|Female| 05165399019|
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1 df.count()
(2) Spark Jobs
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Cmd 8
1 dff=df.distinct()
2 dff.show()
(2) Spark Jobs
dff: pyspark.sql.dataframe.DataFrame = [Name: string, Email_id: string ... 3 more fields]
| Thomas|Thom987@outlook.com| 29| Male| 06896219146|
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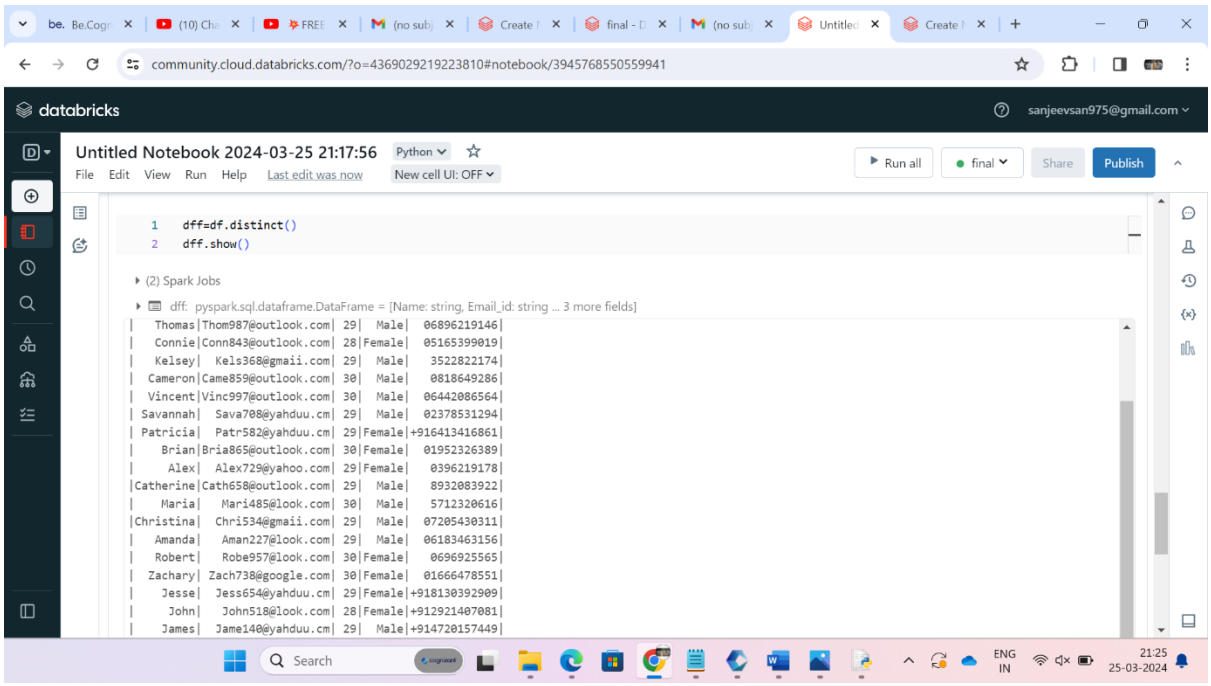
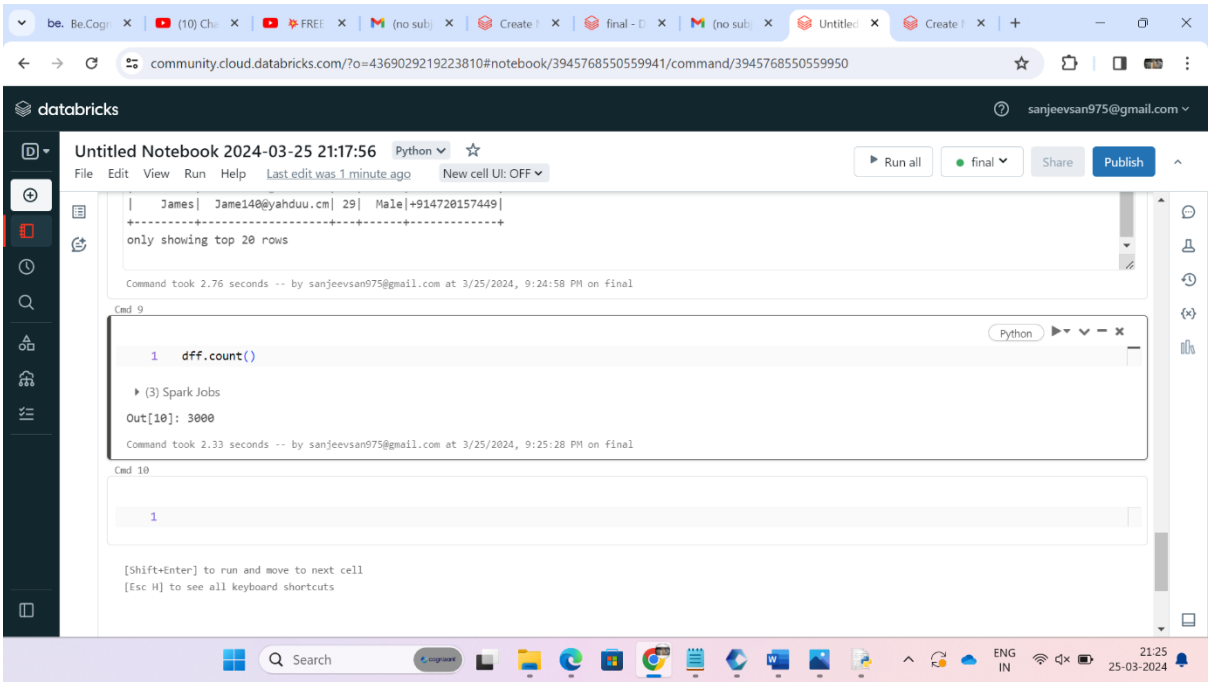
# Distinct Records:

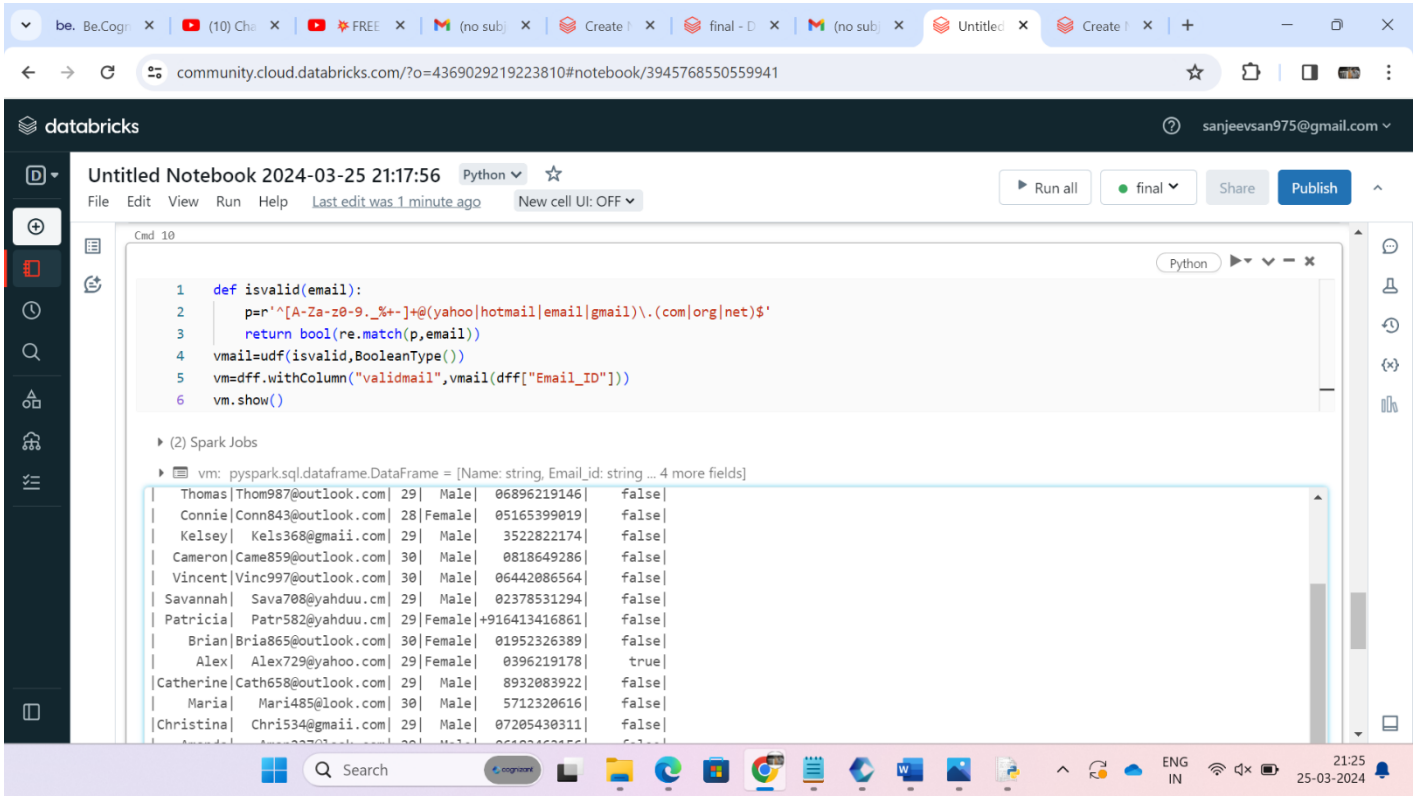
Duplicate records are removed from the DataFrame using the `distinct()` function to ensure each record is unique.



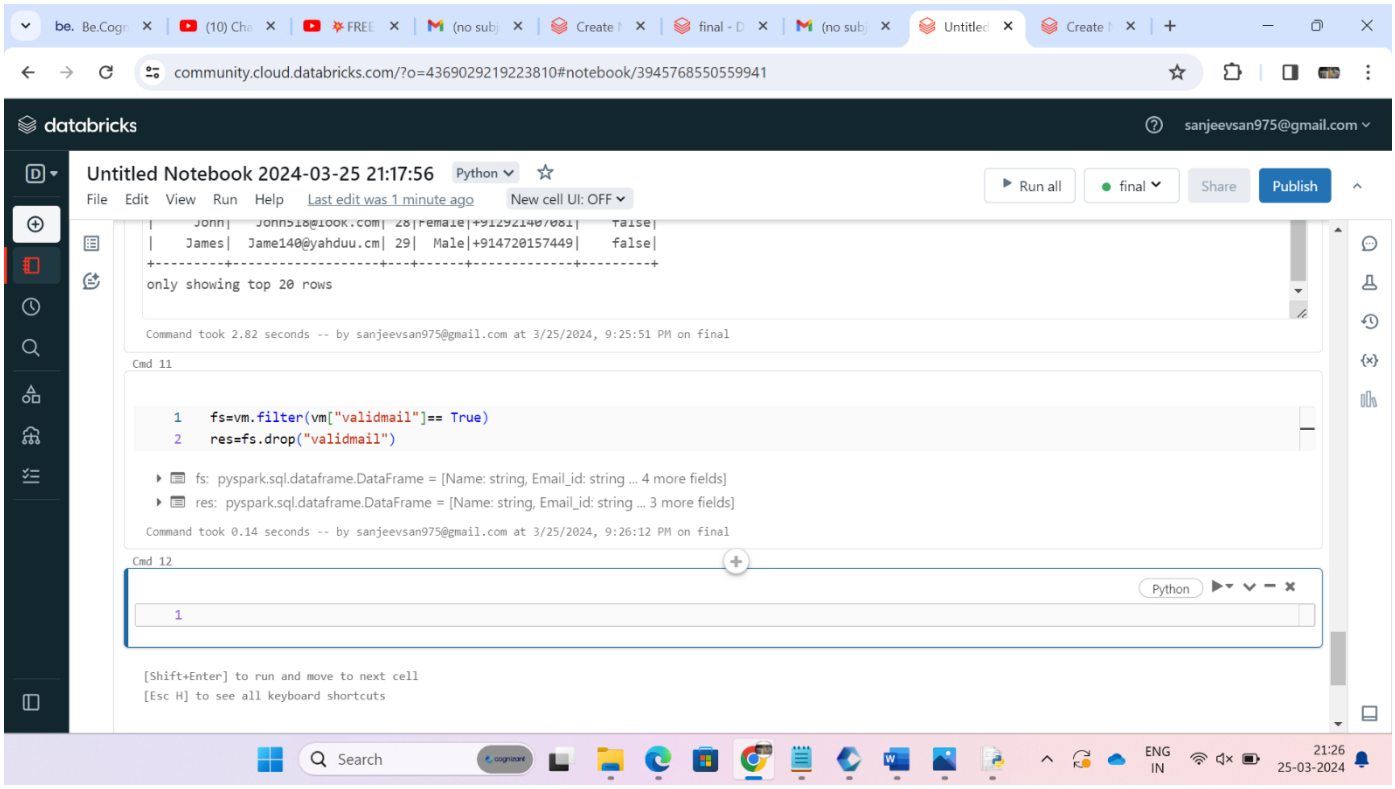
# Email Validation:

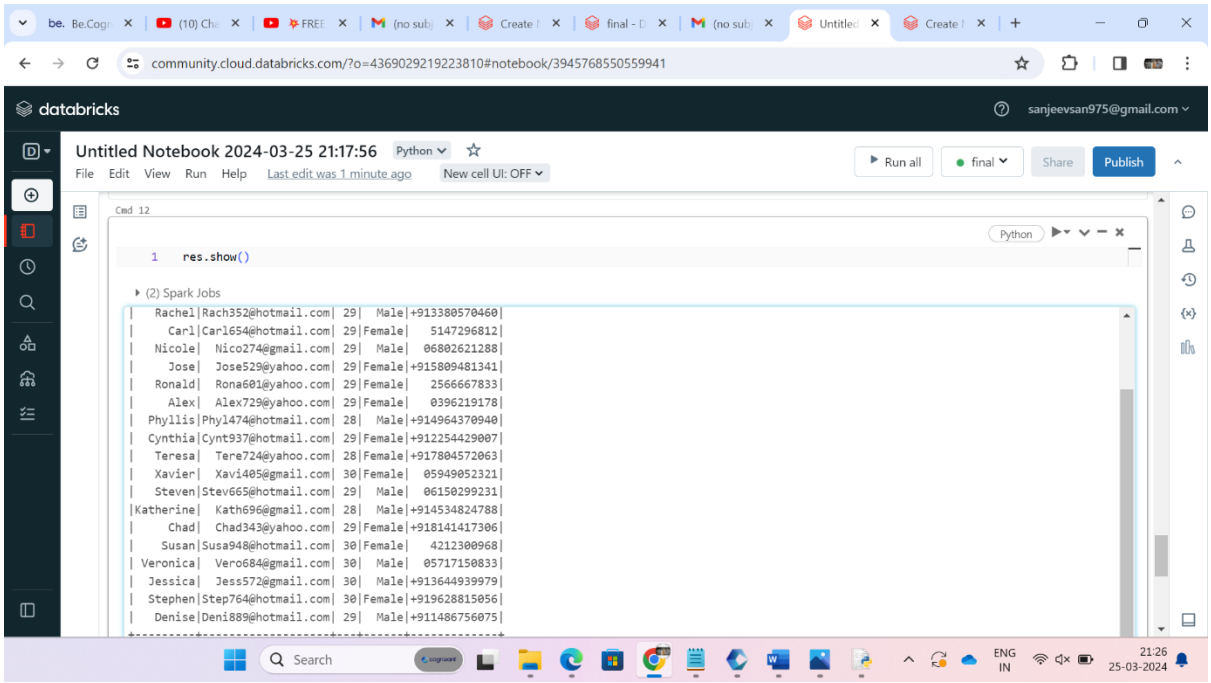
User-defined function (UDF) named `isvalid` is defined to check the validity of email addresses based on a regular expression pattern. This UDF is applied to the DataFrame to create a new column `validmail` indicating whether each email is valid or not.



# Filtering Valid Email Addresses:

Rows with valid email addresses are filtered out from the DataFrame..

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| Carl|Carl654@hotmail.com| 29|Female| 5147296812|
| Nicole| Nico274@gmail.com| 29| Male| 06802621288|
| Jose| Jose529@yahoo.com| 29|Female|+915809481341|
| Ronald| Rona601@yahoo.com| 29|Female| 2566667833|
| Alex| Alex729@yahoo.com| 29|Female| 0396219178|
| Phyllis|Phyl474@hotmail.com| 28| Male|+914964370940|
| Cynthia|Cynt937@hotmail.com| 29|Female|+912254429007|
| Teresa| Tere724@yahoo.com| 28|Female|+917804572063|
| Xavier| Xavi405@gmail.com| 30|Female| 05949052321|
| Steven|Stev665@hotmail.com| 29| Male| 06150299231|
|Katherine| Kath696@gmail.com| 28| Male|+914534824788|
| Chad| Chad343@yahoo.com| 29|Female|+918141417306|
| Susan|Susa948@hotmail.com| 30|Female| 4212300968|
| Veronica| Vero684@gmail.com| 30| Male| 05717150833|
| Jessica| Jess572@gmail.com| 30| Male|+913644939979|
| Stephen|Step764@hotmail.com| 30|Female|+919628815056|
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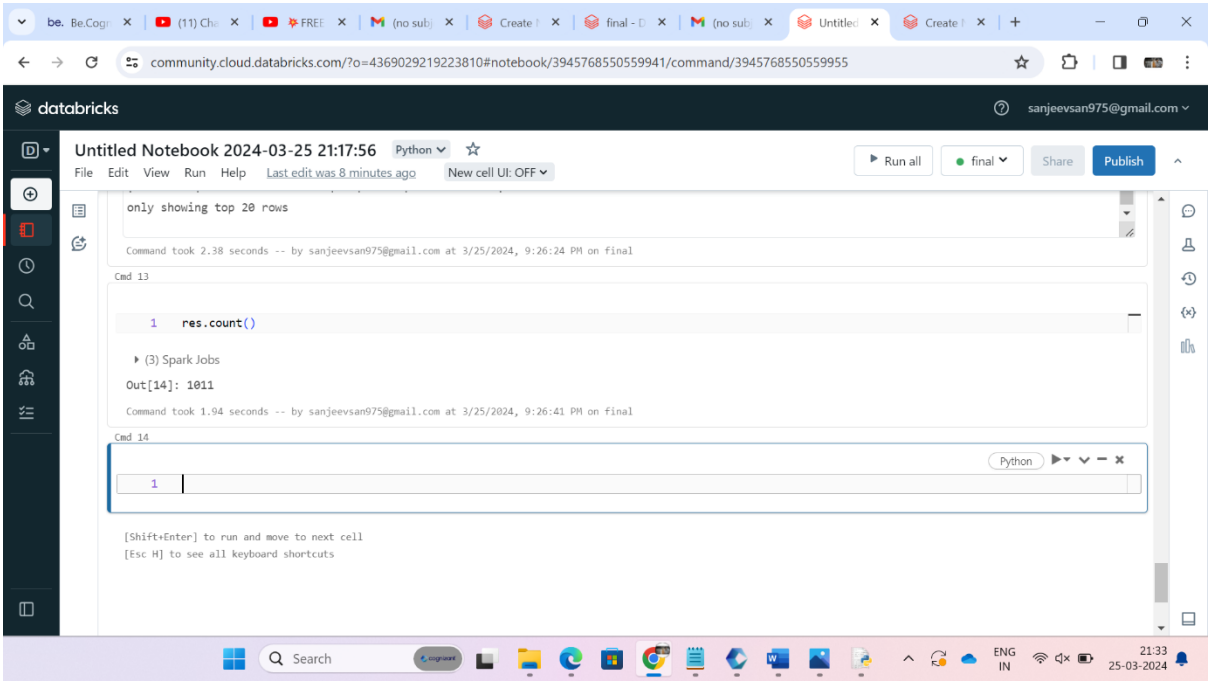
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1 res.count()
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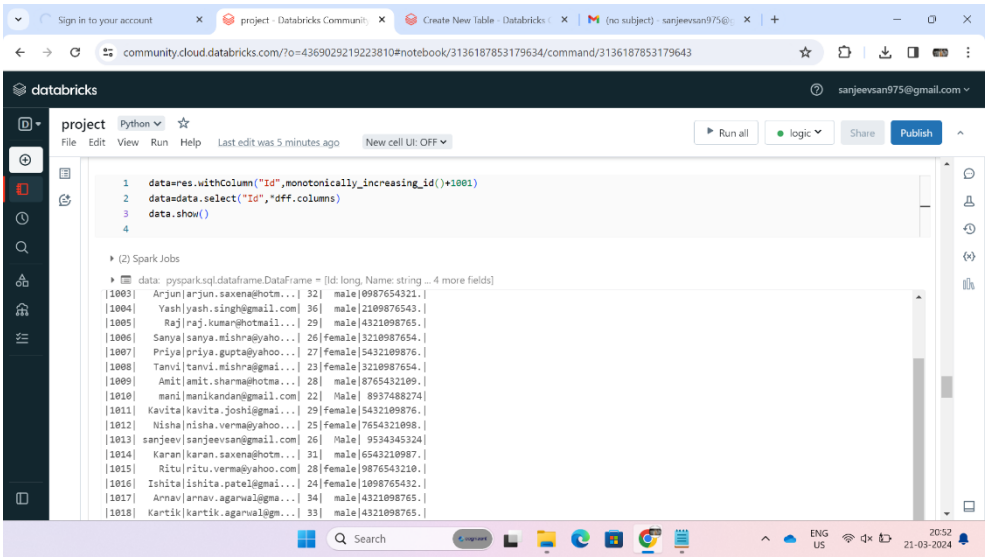
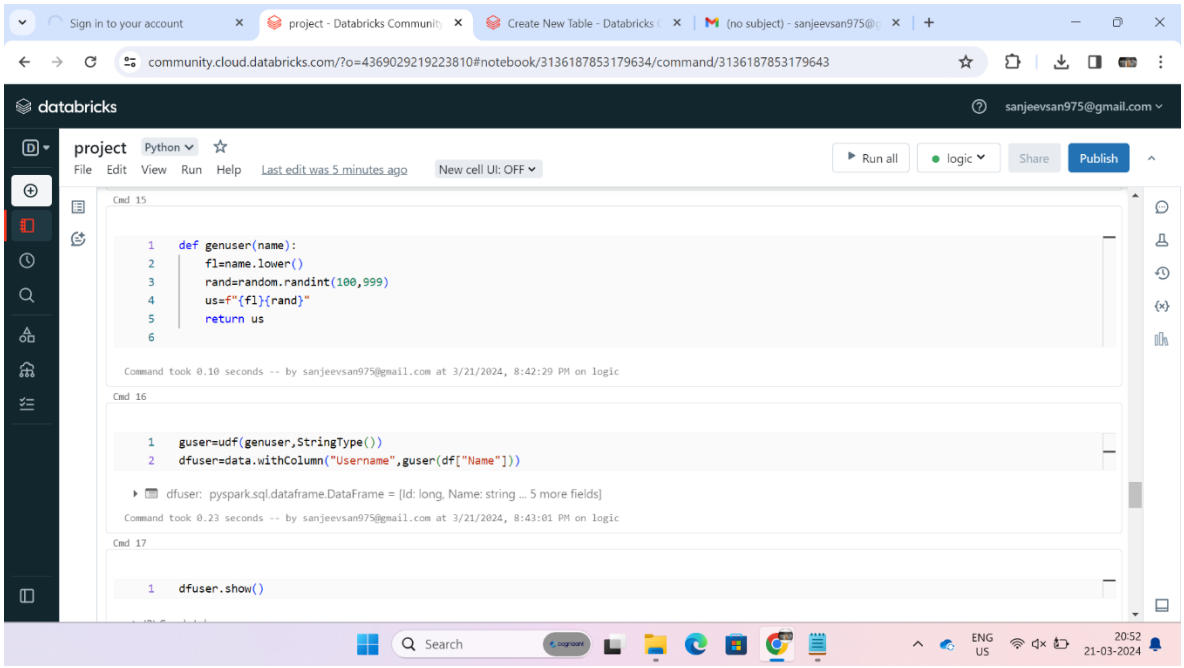
# Adding Unique IDs:

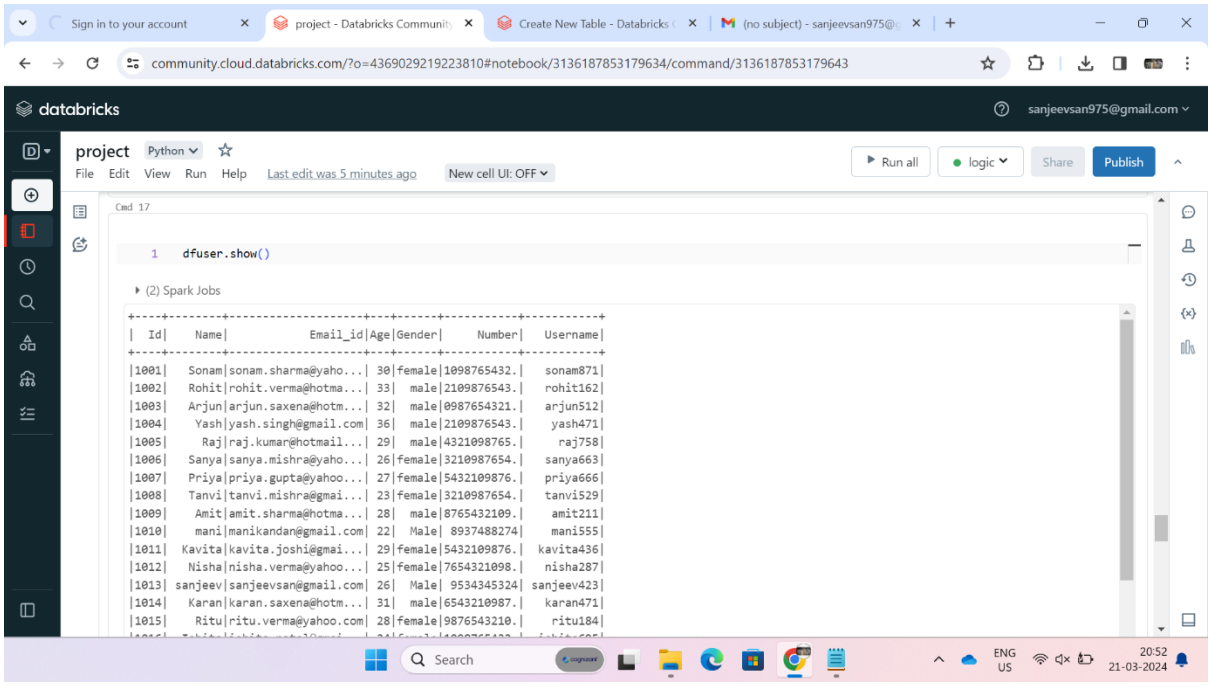
Unique IDs are added to each row using the `monotonically_increasing_id()` function, ensuring each row has a distinct identifier.




# Generating Usernames:

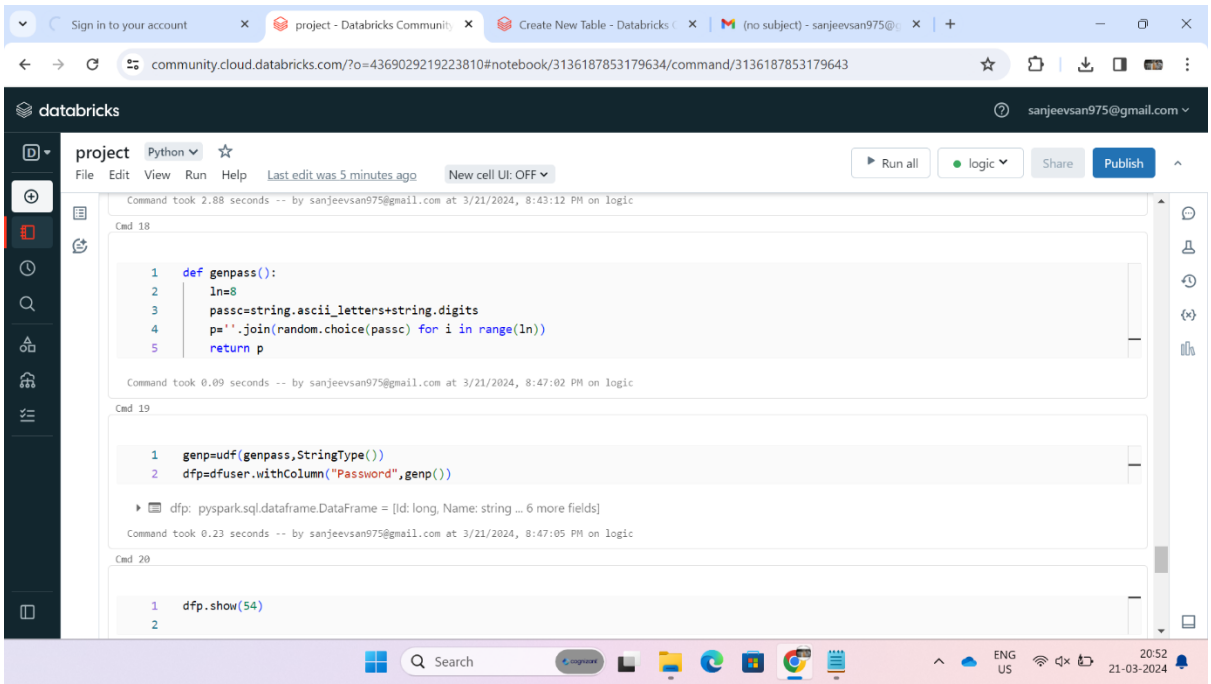
Another UDF named `genuser` is defined to generate usernames based on the lowercased first name and a random integer. This UDF is applied to create a new column `Username`.

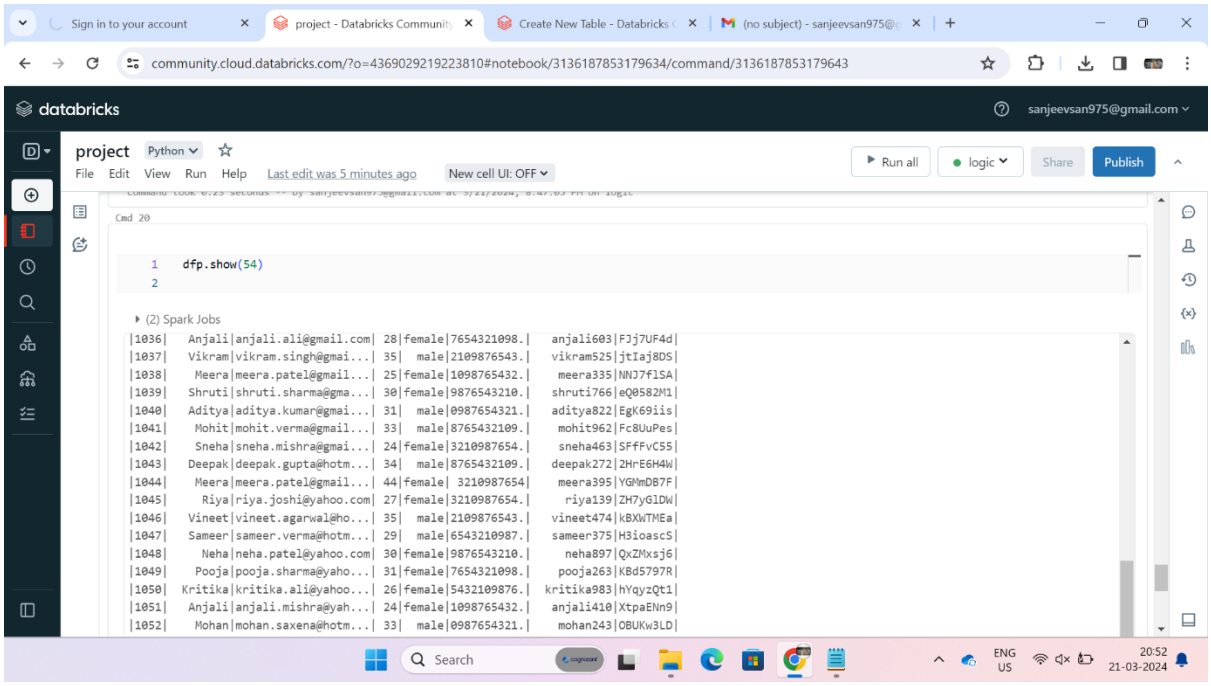





# Generating Passwords:

Similarly, a UDF named `genpass` is defined to generate random passwords consisting of letters and digits. This UDF is applied to create a new column `Password`






# Loading to MySQL Cloud:

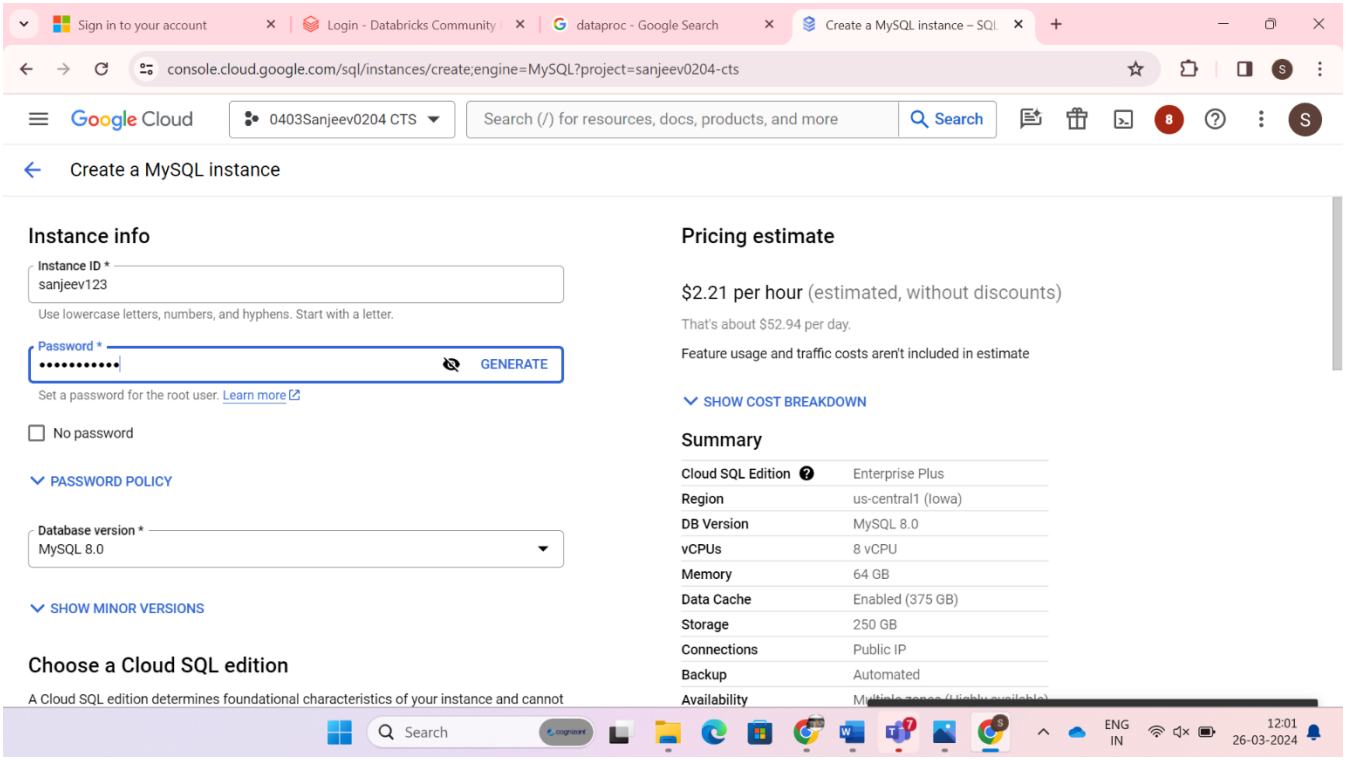
Finally, the processed DataFrame (`dfp`) is written to a MySQL database table specified by the `table` parameter using JDBC connection parameters such as driver, URL, username, and password. The data is appended to the table in the database.

For that we are creating a google cloud SQL for loading a data.

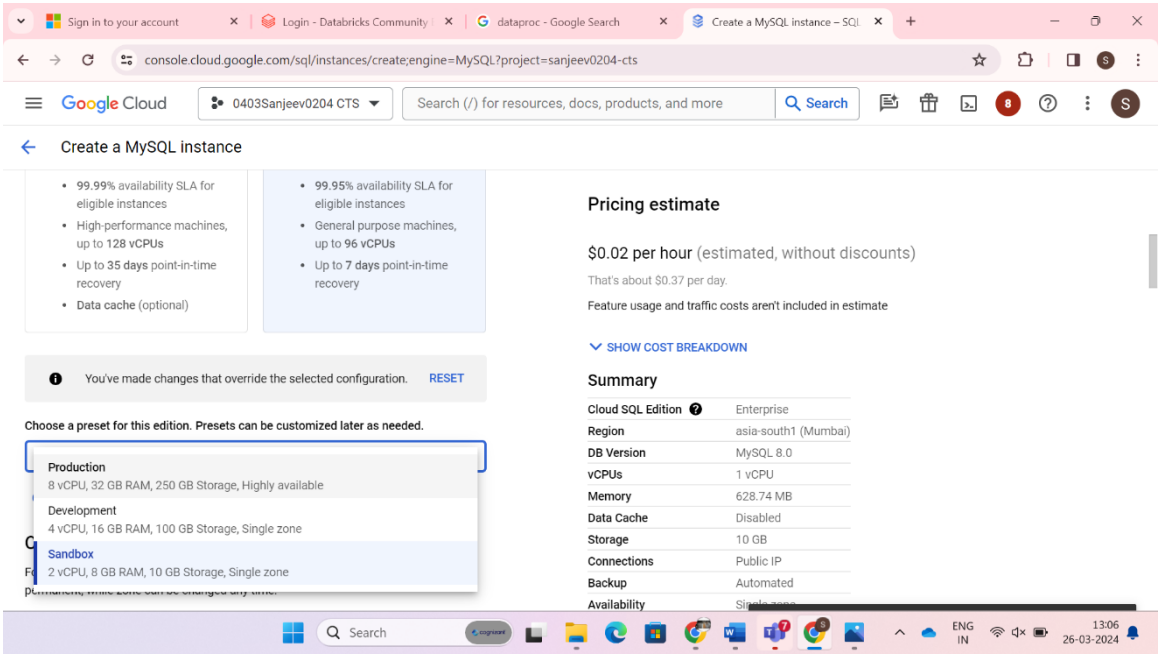
MySQL in the cloud offers scalability, managed services, high availability, global accessibility, and cost efficiency. It easily scales to accommodate growing data needs, freeing up time with managed services for backups, maintenance, and updates. High availability features ensure uptime and data durability, while global accessibility fosters collaboration. Cost efficiency stems from a pay-as-you-go model.

Conversely, local MySQL provides performance advantages, data control, predictable costs, customization, and offline access. It offers faster query execution, control over infrastructure, predictable costs, customization options, and ensures uninterrupted access in environments with limited internet connectivity. Organizations often choose based on needs, budget, and regulatory requirements.

## 1)Create instance in Mysql cloud:

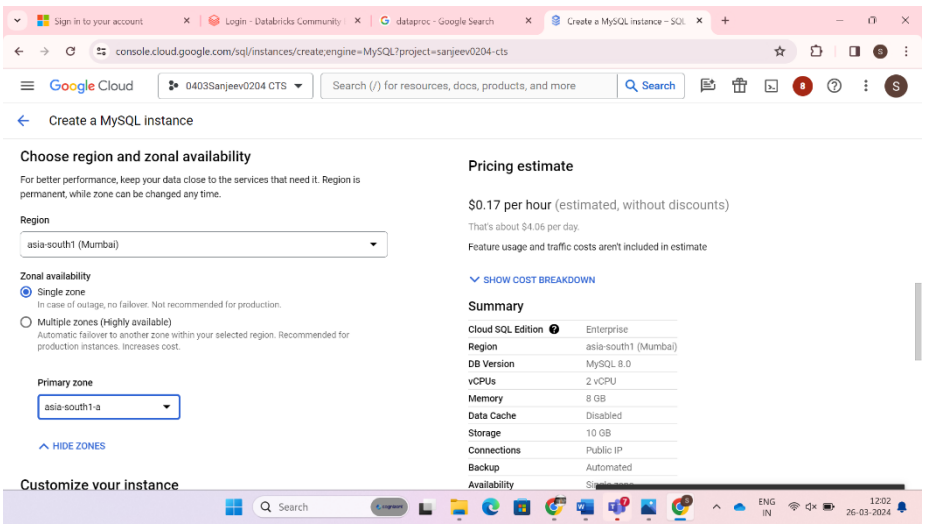


**2) Compare to other production sandbox is less in features and prize.**




# Region and zone:

A region is a specific geographical location where you can run your resources. Each region is subdivided into several zones. For example, the us-central1 region in the central United States has zones us-central1-a , us-central1-b , us-central1-c , and us-central1-f .



## 3) Shared Core (vCPU) Instances and Dedicated Core (vCPU) Instances:

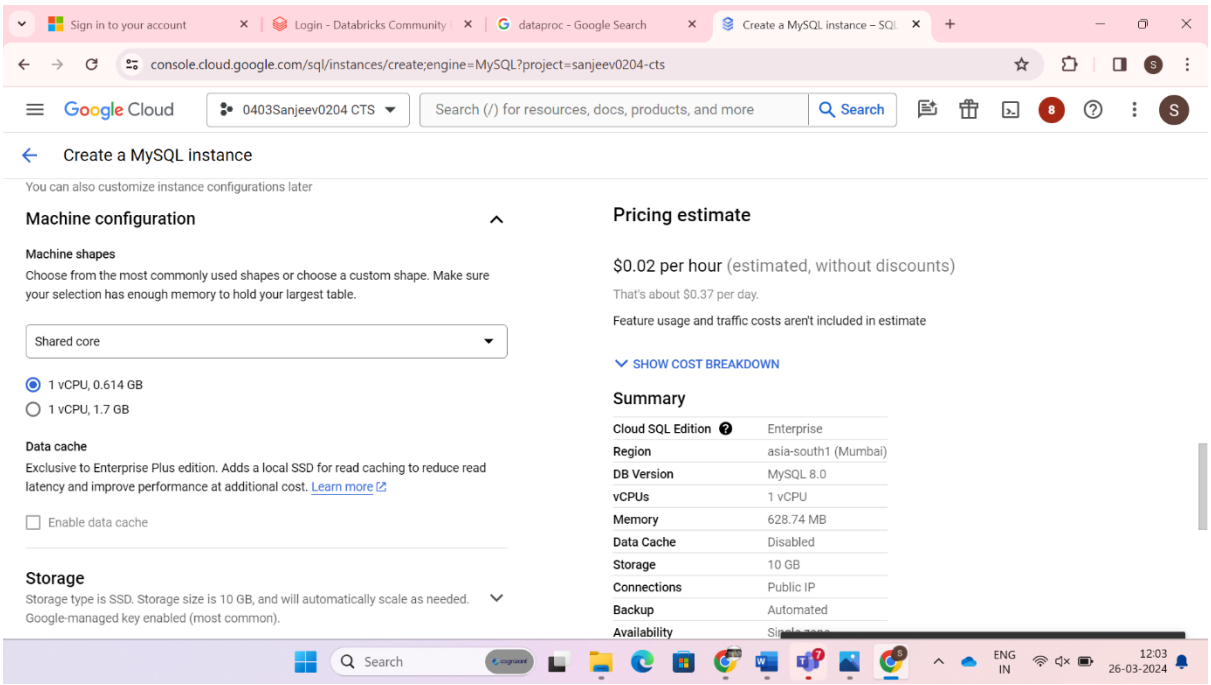
**Shared Core (vCPU) Instances**:

- Shared-core machine types provide **one virtual CPU** that runs for a portion of the time on a single hardware hyper-thread of the host CPU.
- These instances are **cost-effective** for running small, non-resource-intensive applications.

**Dedicated Core (vCPU) Instances**:

- In contrast, dedicated core instances allocate **exclusive CPU resources** to your virtual machine.
- Each core is reserved for your instance, ensuring consistent performance and security.

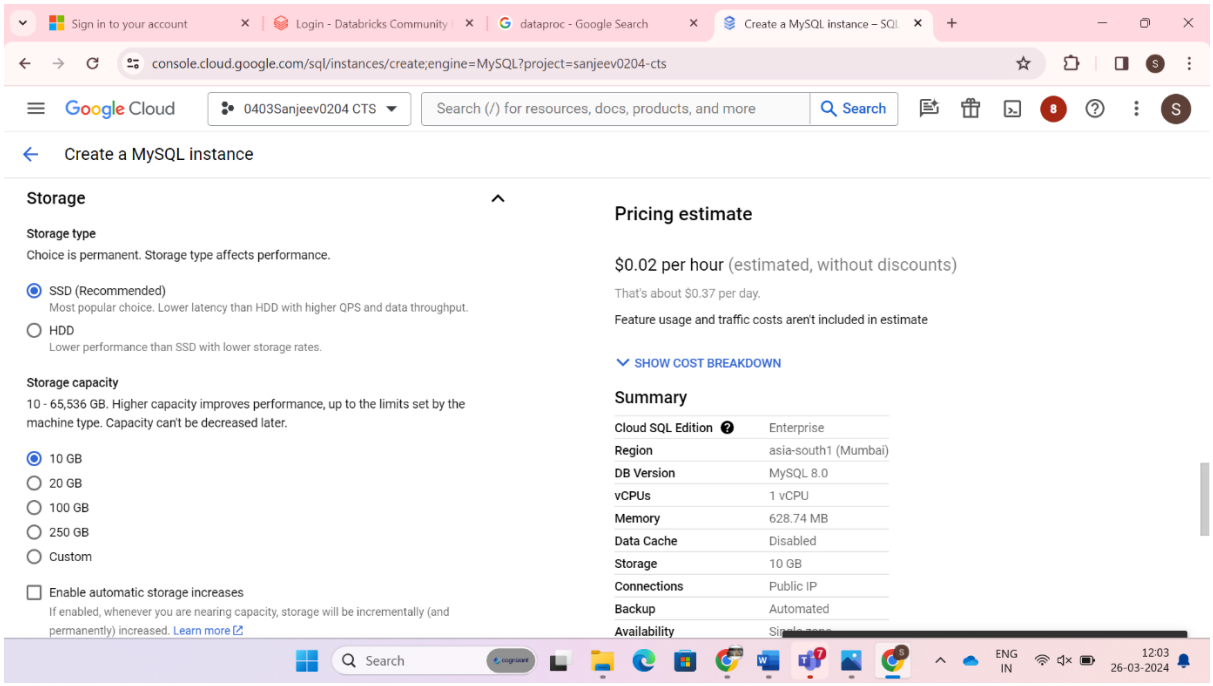
So, we using shared core for cost-effective



## 4) Storage SSD or HDD:

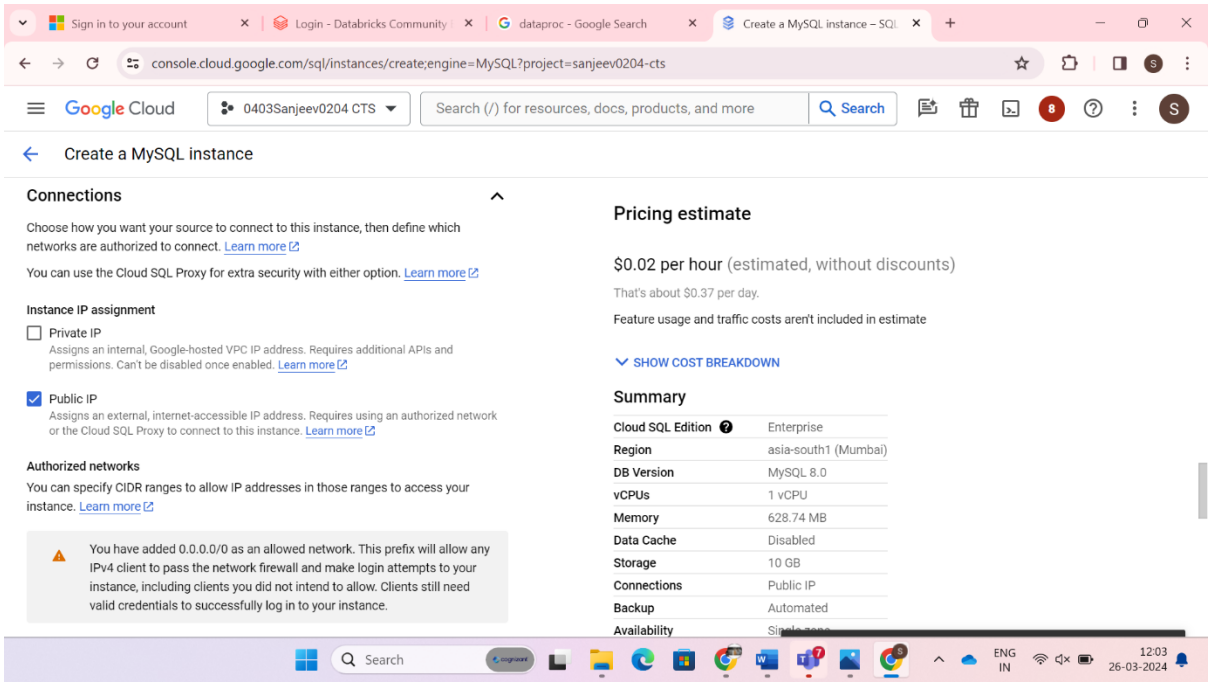
Solid state drives (SSDs) typically use flash-based memory to store data and thus have no moving parts. They have faster read/write speeds than HDDs, lower access times (less latency), and a higher cost per gigabyte of storage.

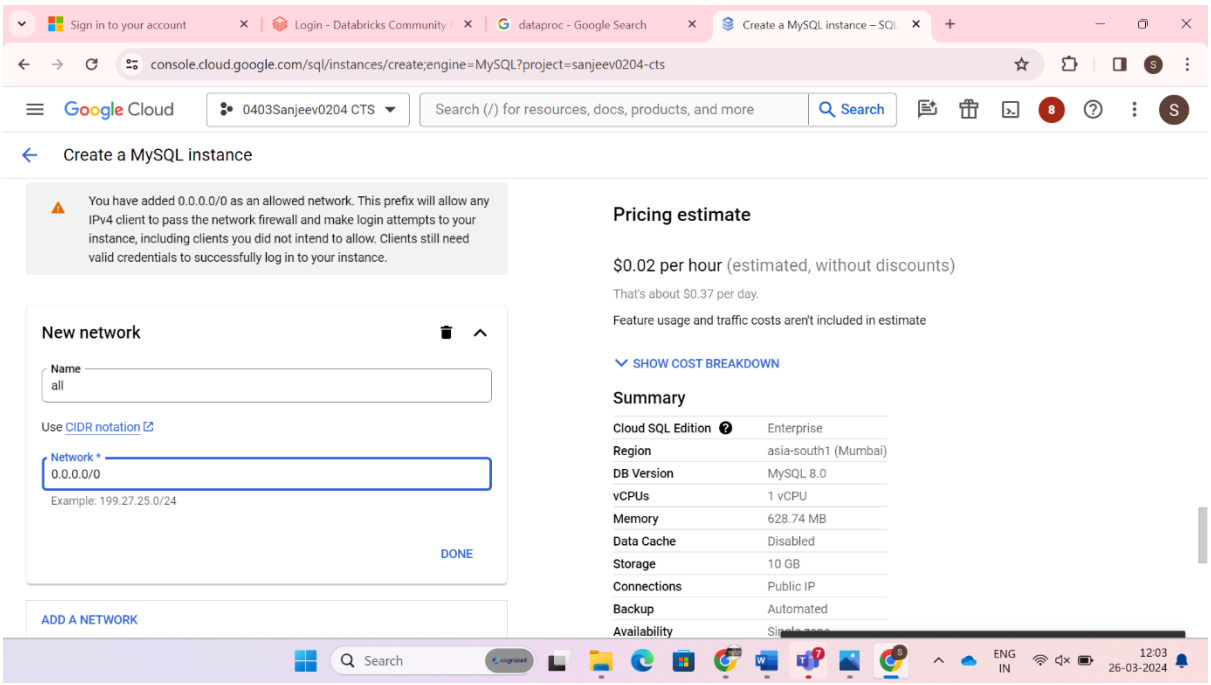
So, we choose SSD.




## 5) Network connection :

A public IP address is a unique IP address assigned to your network router by your internet service provider and can be accessed directly over the internet. A private IP address is a unique address that your network router assigns to your device. It is used within a private network to connect securely to other devices.


Sign in to your account
Login - Databricks Community
dataproc - Google Search
Create a MySQL instance – SQL
console.cloud.google.com/sql/instances/create;engine=MySQL?project=sanjeev0204-cts
Google Cloud
0403Sanjeev0204 CTS
Search (/) for resources, docs, products, and more
Search
Create a MySQL instance
Connections
Choose how you want your source to connect to this instance, then define which networks are authorized to connect. Learn more
You can use the Cloud SQL Proxy for extra security with either option. Learn more
Instance IP assignment
Private IP
Assigns an internal, Google-hosted VPC IP address. Requires additional APIs and permissions. Can't be disabled once enabled. Learn more
Public IP
Assigns an external, internet-accessible IP address. Requires using an authorized network or the Cloud SQL Proxy to connect to this instance. Learn more
Authorized networks
You can specify CIDR ranges to allow IP addresses in those ranges to access your instance. Learn more
You have added 0.0.0.0/0 as an allowed network. This prefix will allow any IPv4 client to pass the network firewall and make login attempts to your instance, including clients you did not intend to allow. Clients still need valid credentials to successfully log in to your instance.
Pricing estimate
$0.02 per hour (estimated, without discounts)
That's about $0.37 per day.
Feature usage and traffic costs aren't included in estimate
SHOW COST BREAKDOWN
Summary
Cloud SQL Edition Enterprise
Region asia-south1 (Mumbai)
DB Version MySQL 8.0
vCPUs 1 vCPU
Memory 628.74 MB
Data Cache Disabled
Storage 10 GB
Connections Public IP
Backup Automated
Availability
Search
ENG IN
12:03 26-03-2024


Sign in to your account
Login - Databricks Community
dataproc - Google Search
Create a MySQL instance – SQL
console.cloud.google.com/sql/instances/create;engine=MySQL?project=sanjeev0204-cts
Google Cloud
0403Sanjeev0204 CTS
Search (/) for resources, docs, products, and more
Search
Create a MySQL instance
You have added 0.0.0.0/0 as an allowed network. This prefix will allow any IPv4 client to pass the network firewall and make login attempts to your instance, including clients you did not intend to allow. Clients still need valid credentials to successfully log in to your instance.
New network
Name
all
Use CIDR notation
Network *
0.0.0.0/0
Example: 199.27.25.0/24
DONE
ADD A NETWORK
Pricing estimate
$0.02 per hour (estimated, without discounts)
That's about $0.37 per day.
Feature usage and traffic costs aren't included in estimate
SHOW COST BREAKDOWN
Summary
Cloud SQL Edition Enterprise
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Data Cache Disabled
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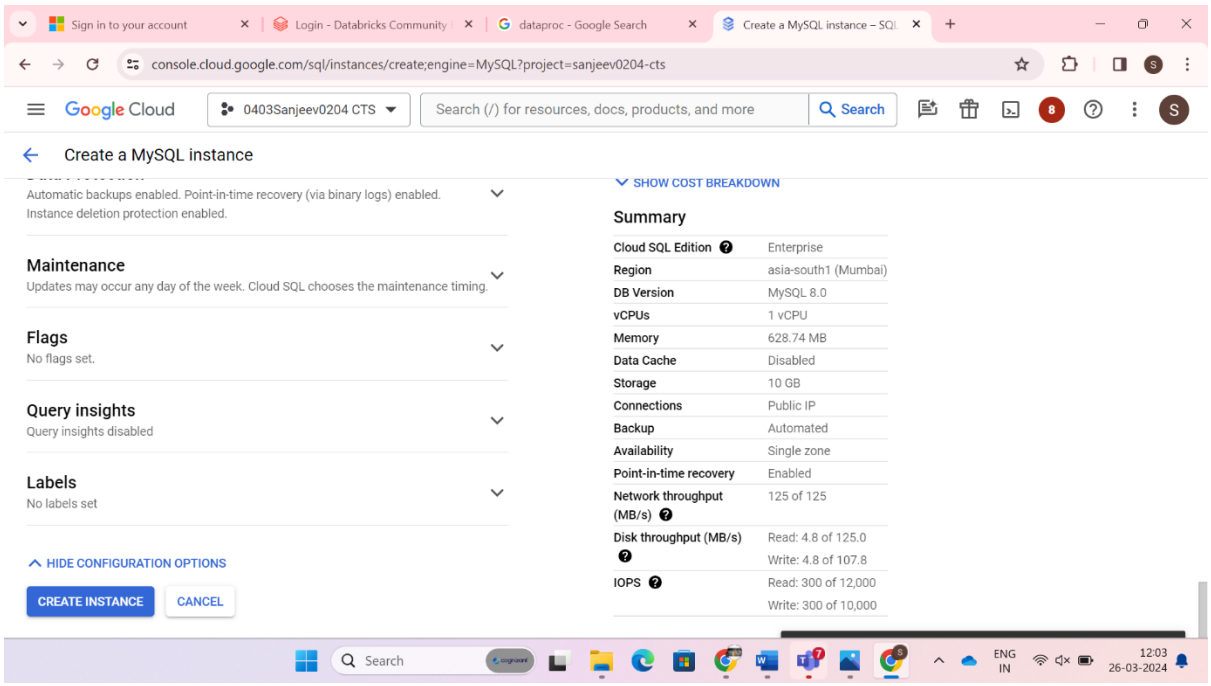
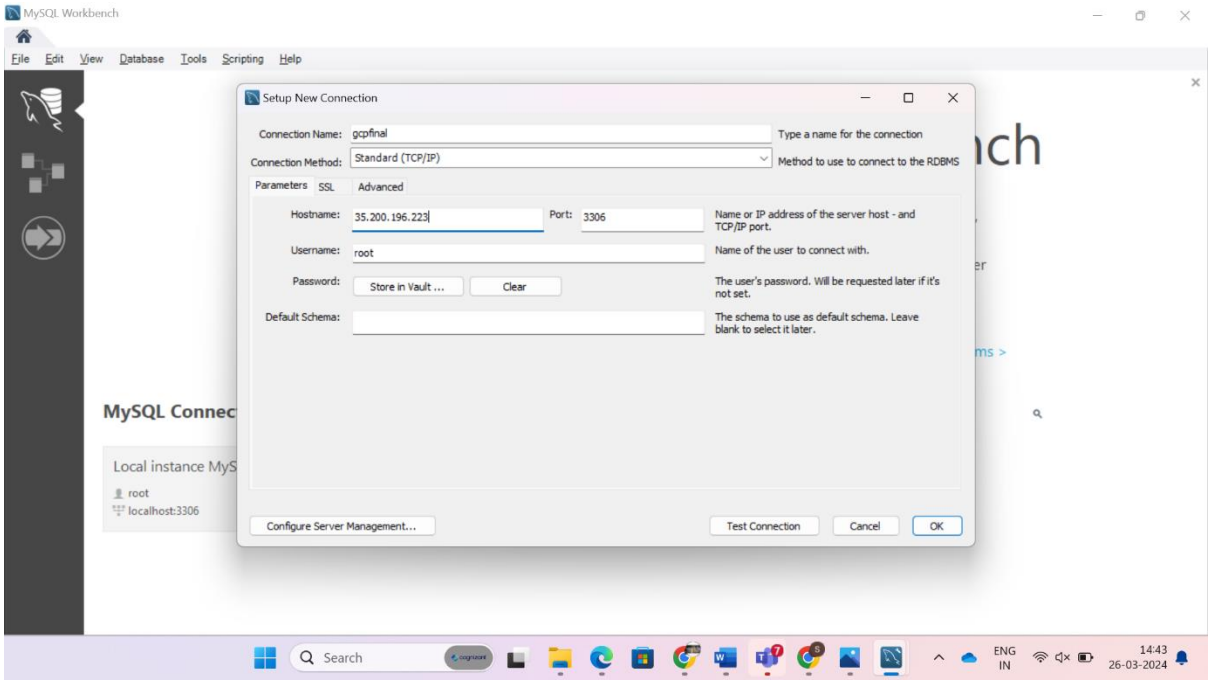
Backup Automated
Availability
Search
ENG IN
12:03 26-03-2024

## 6) Then create a instance:

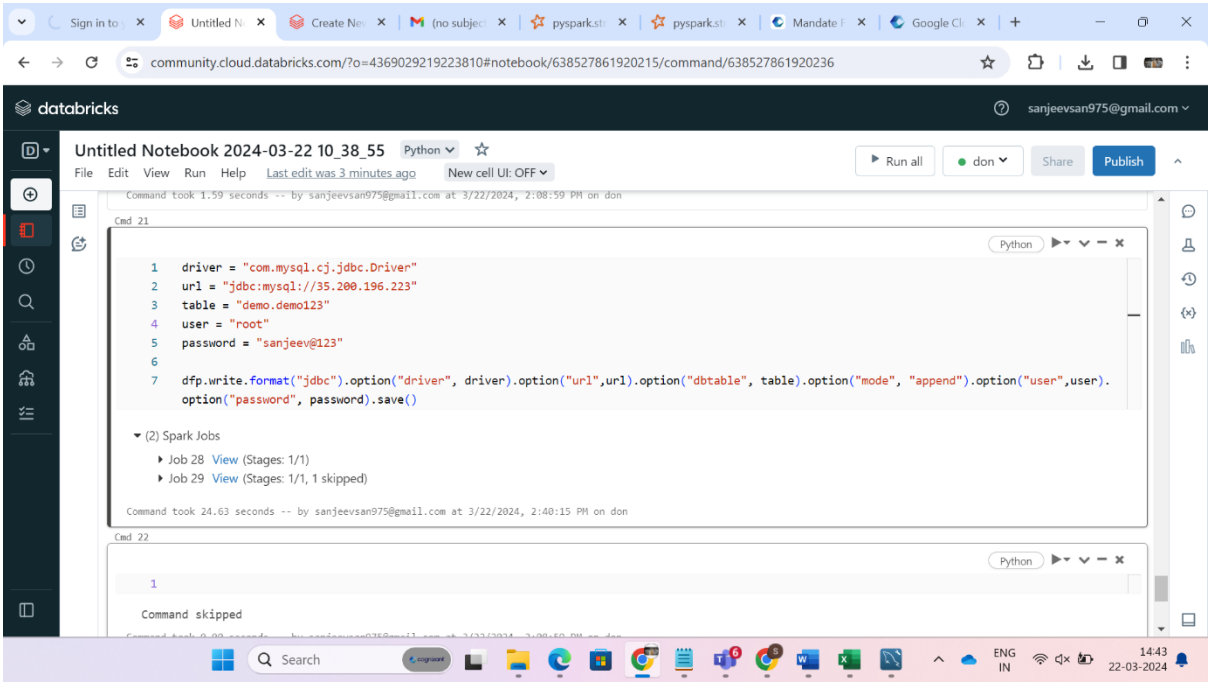



Now MySql instance is create,

1) Open mysql work bench.
2) And open setup new connections and enter a connection name. And Hostname in that we need give mysql instance pubile IP address.
3) Enter a password what we are given in mysql instance.
4) And check for the connection After the successful connection.
5) Then open the mysql work bench and create a database as “demo”.

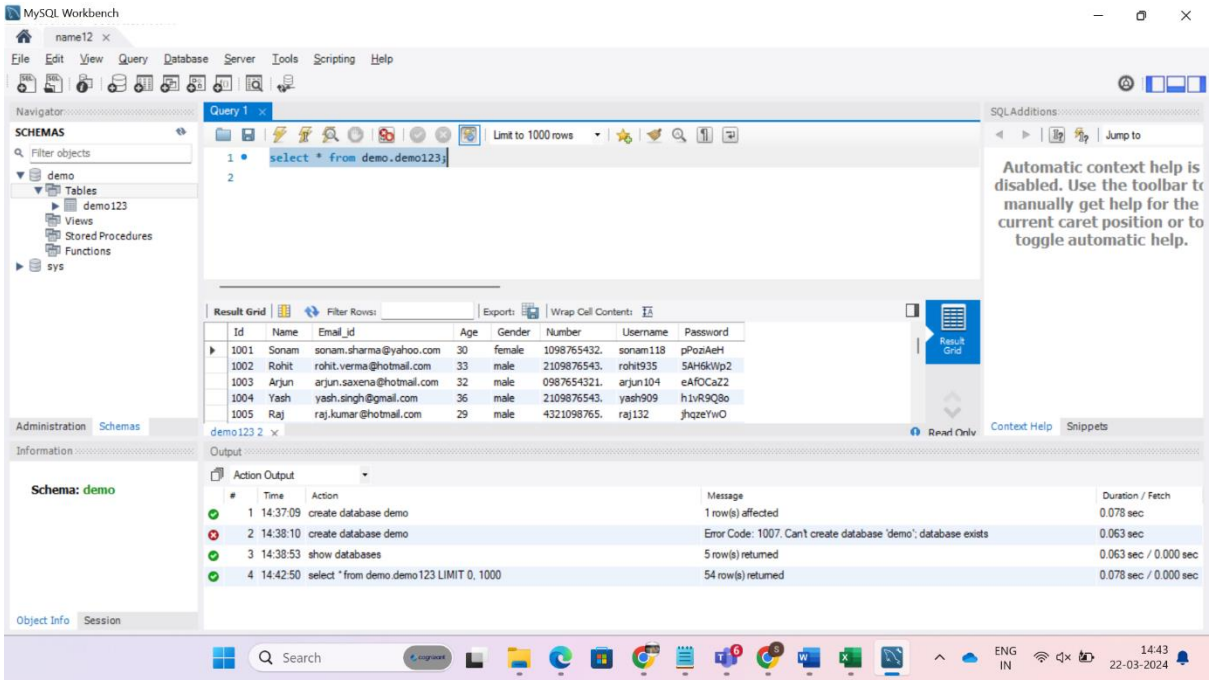


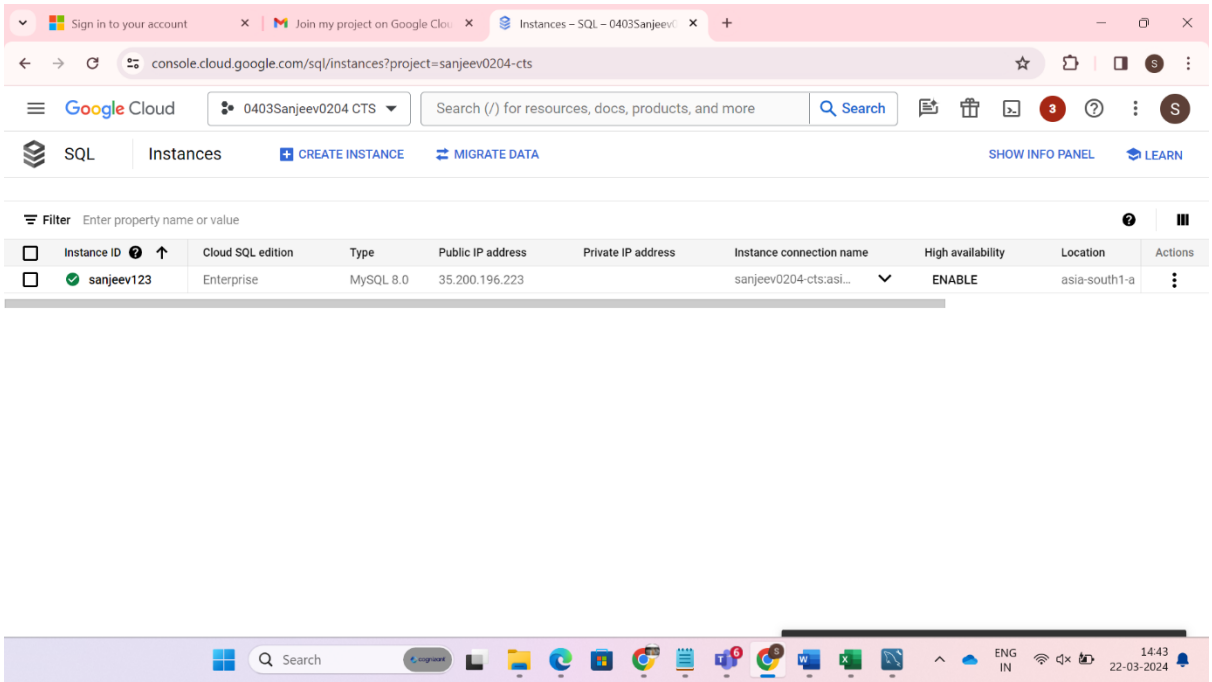

- We have a code to connect Mysql cloud to Databricks.
- Now we need to give IP address in URL.
- Enter database name and table name in table row.
- Then enter the password and run the program.



# Check load data in Mysql cloud:

- Open Mysql work bench and enter the command. Using select statement.
- You will the loaded data.



# Chapter-3

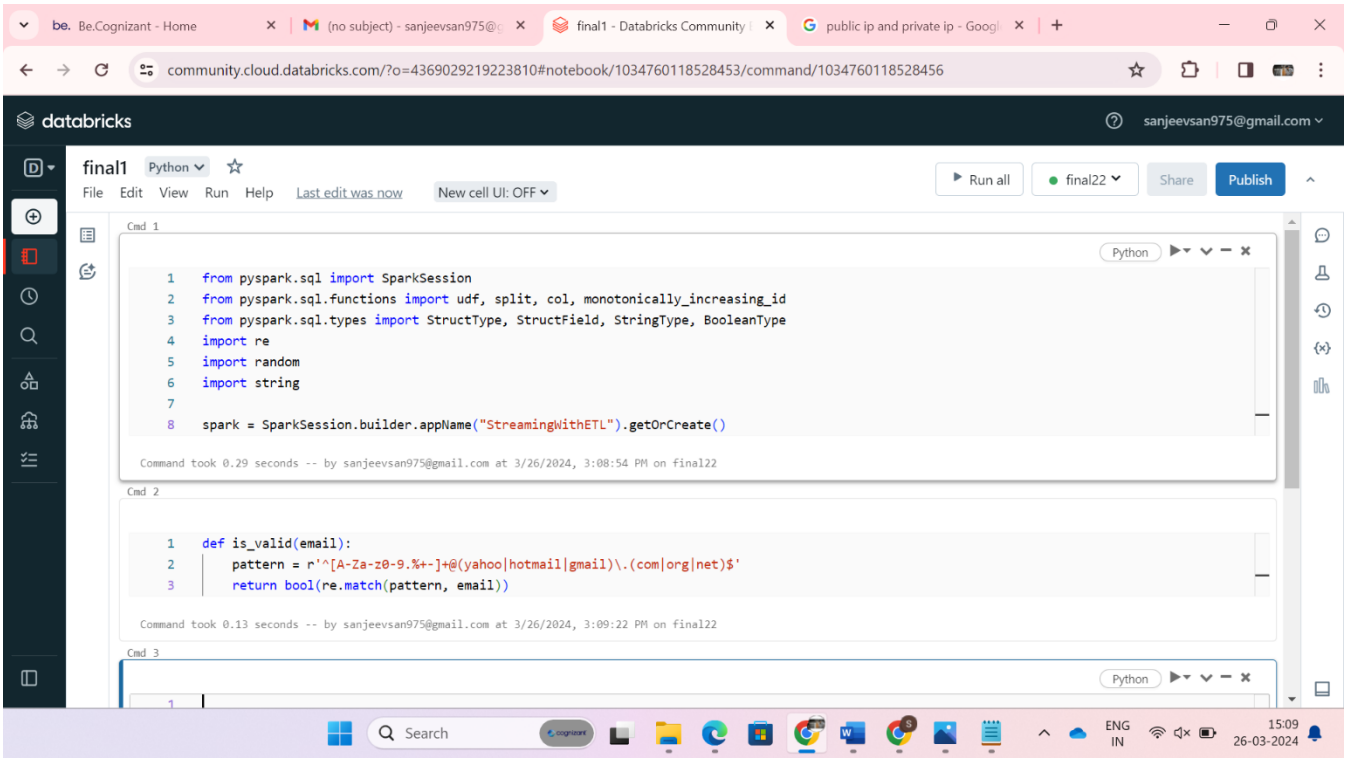
# STREAMING USING ETL:

## 1)Imports:

It imports necessary modules and functions from PySpark, such as SparkSession, udf, split, col, monotonically_increasing_id, StructType, StructField, StringType, BooleanType, as well as standard Python modules like re (regular expressions), random, and string.

## 2)SparkSession:

It creates a SparkSession named "StreamingWithETL" or retrieves an existing one if available

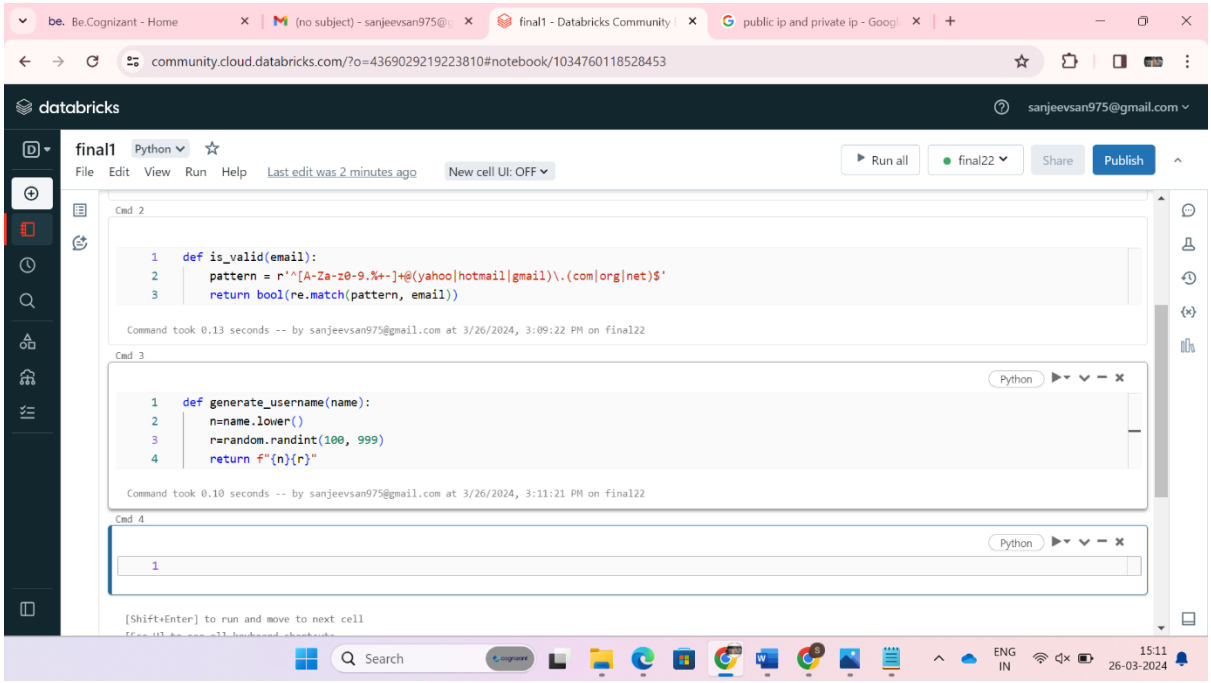


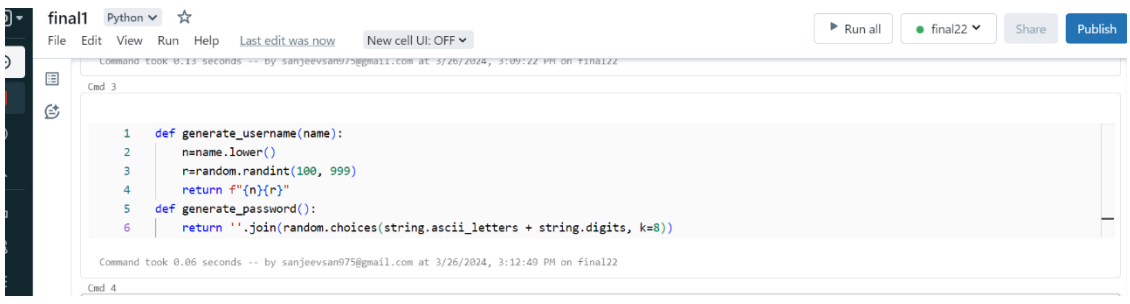
# 3) User-Defined Functions (UDFs):

-**`is_valid`:** A function to validate email addresses based on a regular expression pattern.

- **`generate_username`:** A function to generate a username from a given name.

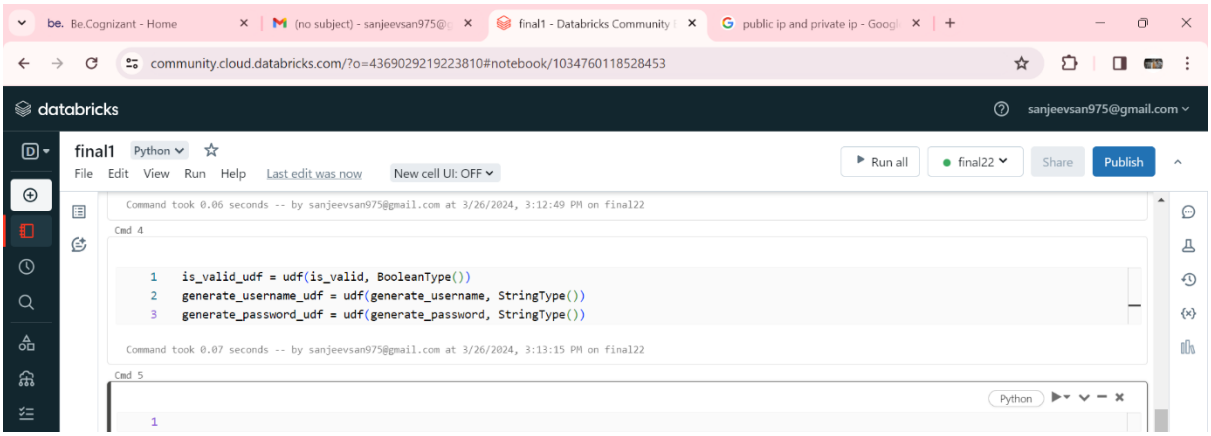
- **`generate_password`:** A function to generate a random password.



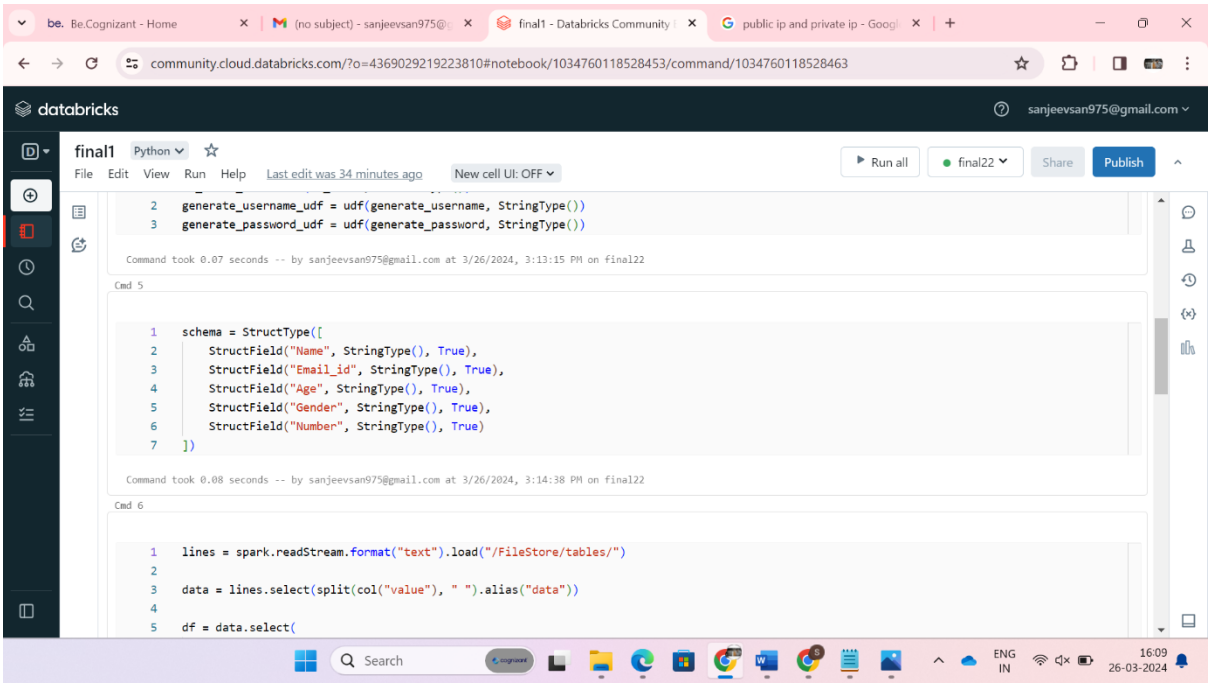
# 4) UDF Registration:

Registers the UDFs using the `udf` function provided by PySpark.




# 5) Schema Definition:

Defines the schema for the structured streaming data. The schema includes fields for "Name", "Email id", "Gender", and "Number".

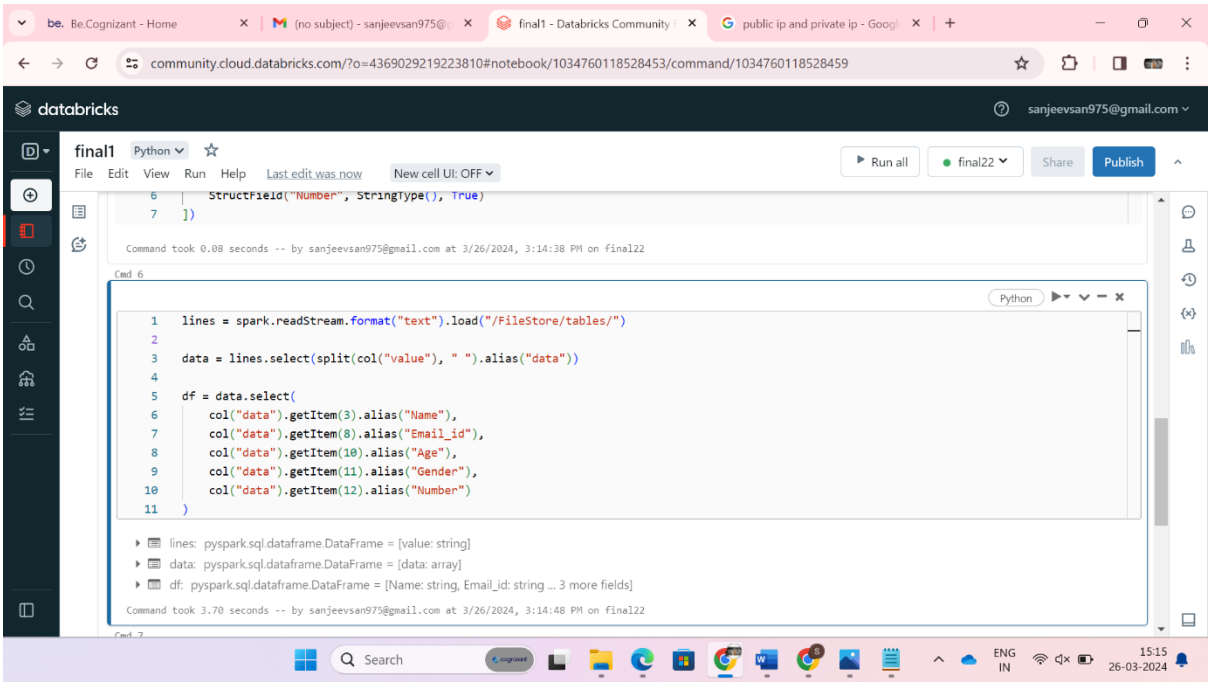


## 6) Reading Stream:

- Reads streaming data from a specified location ("/FileStore/tables/") as text files.

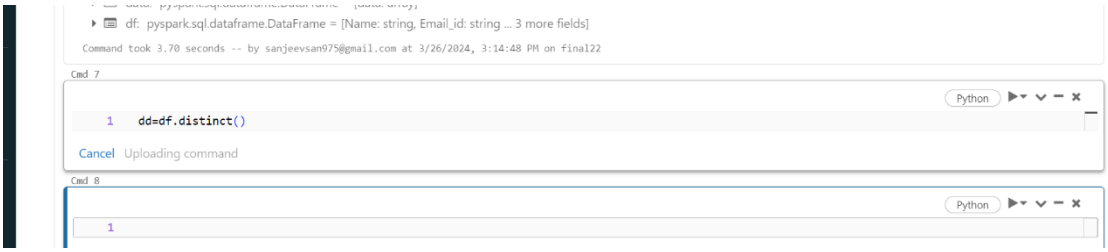
# Data Transformation:

- Splits the lines into columns using the `split` function and assigns the result to a column named "data".
  - Selects specific columns from the "data" column to create a DataFrame (`df`) with columns "Name", "Email_id", "Age", "Gender", and "Number".



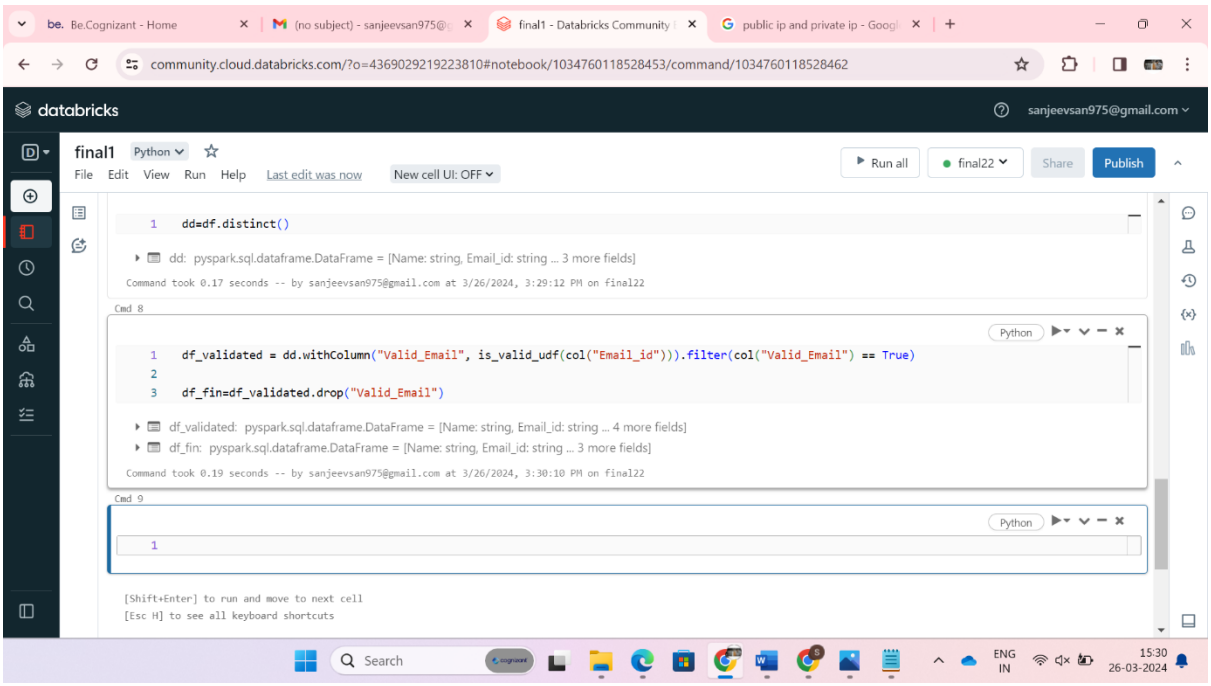

## 7) Data Deduplication:

- Removes duplicate records from the DataFrame (`df`) using the `distinct` method.



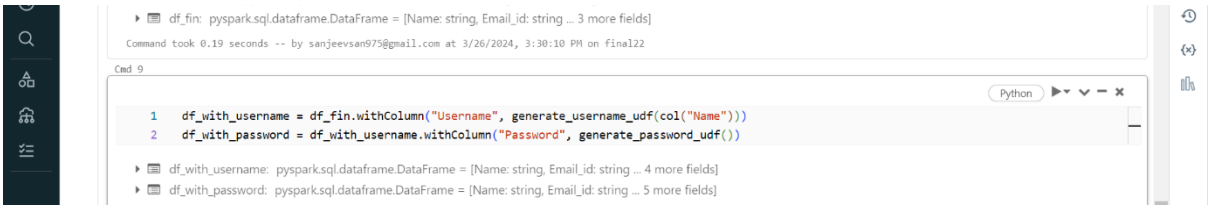
# 8) Data Validation:

- Adds a column "Valid Email" to indicate whether the email addresses are valid by applying the `is_valid_udf` function.
- Filters out rows where the email address is valid.
- Drops the "Valid_Email" column from the DataFrame



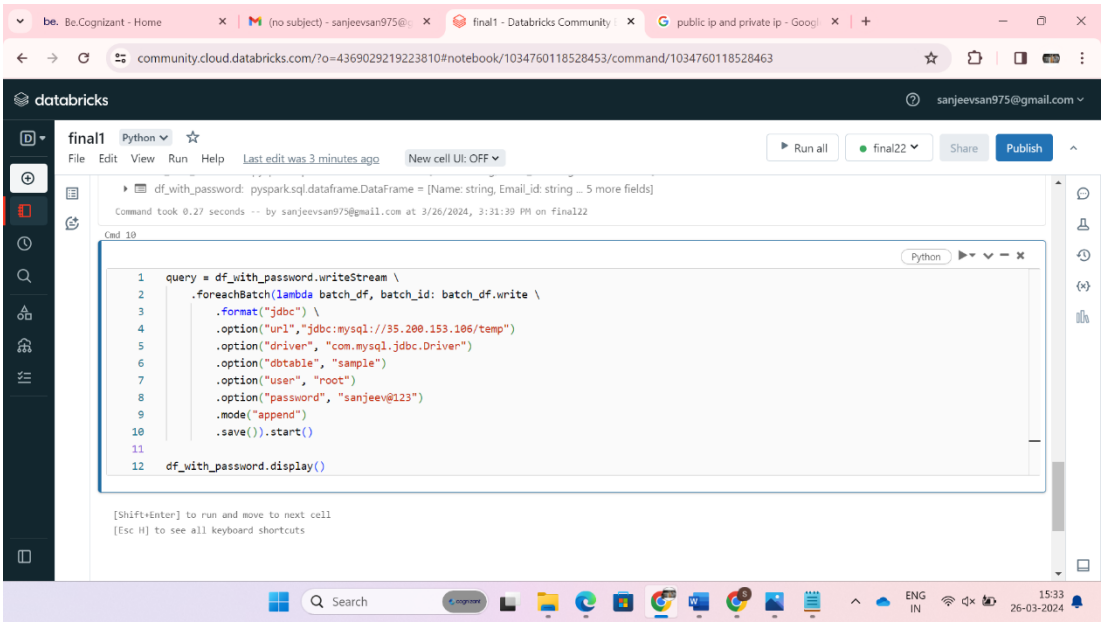

# Additional Data Transformation:

- Adds a "Username" column by applying the `generate_username_udf` function.
- Adds a "Password" column by applying the `generate_password_udf` function.

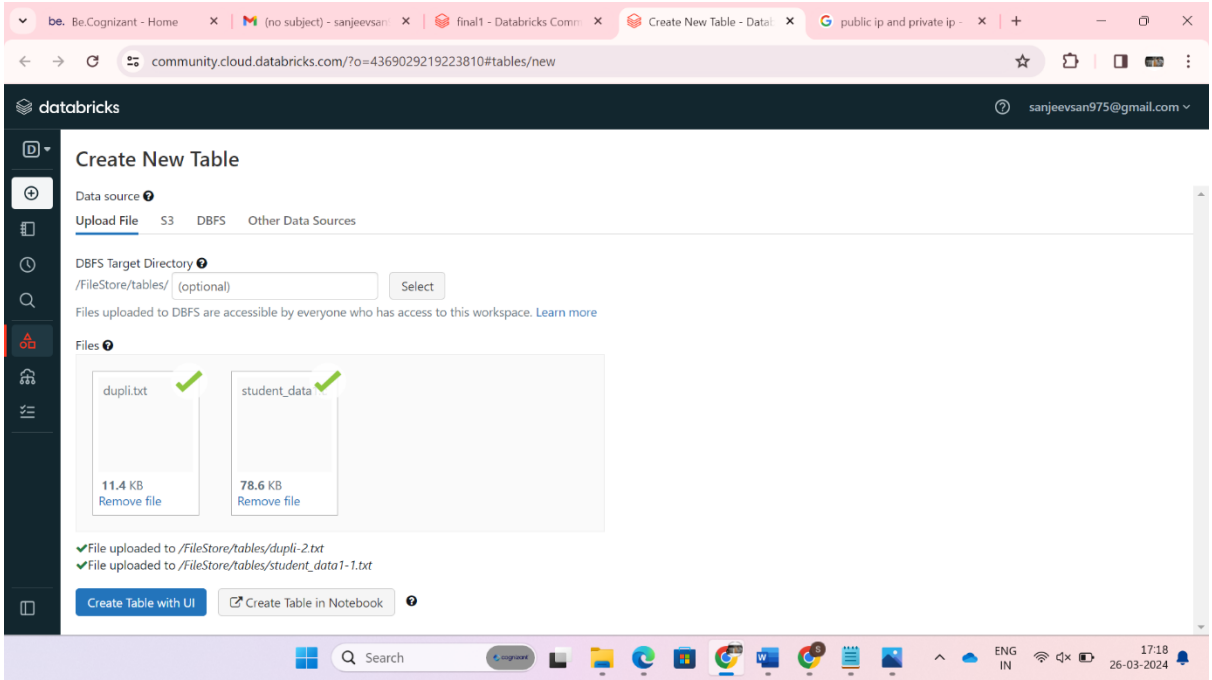


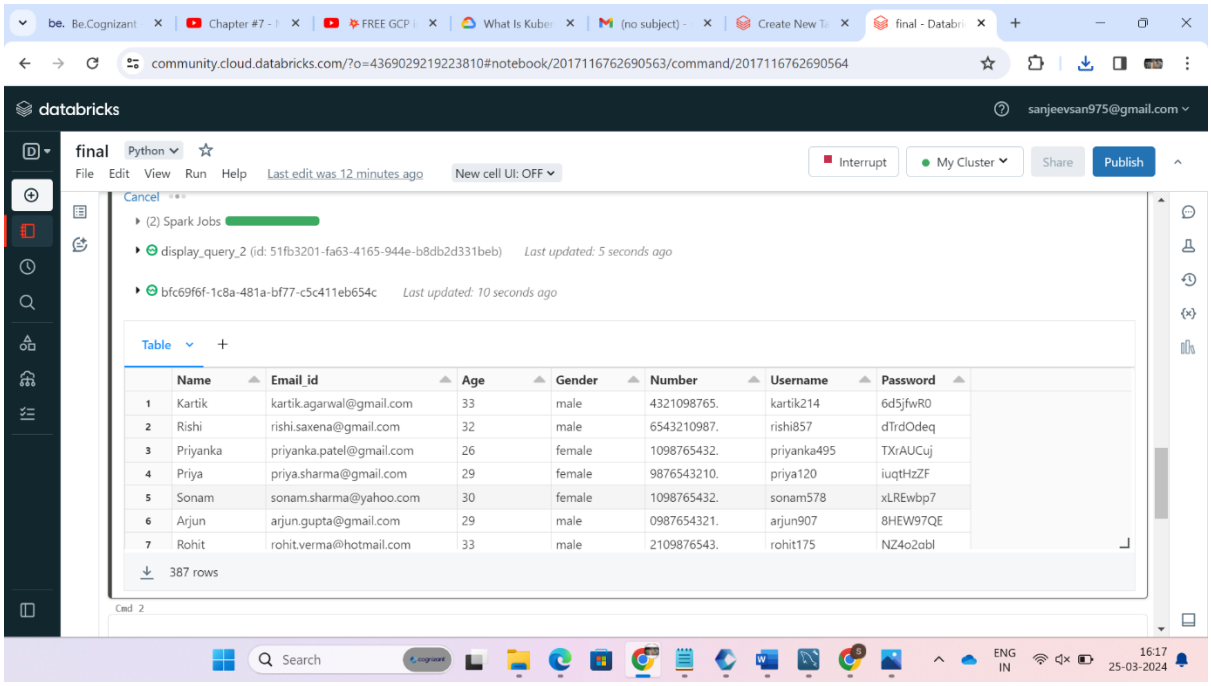
# 9) Writing to Sink in MySQL Cloud:

- Writes the processed data to a JDBC sink (MySQL Cloud) using a foreach Batch writer.
- Specifies connection parameters such as URL IP Address, table name, username, and password.
- Create mysql instance in cloud.
-In mysql workbench create new connection and link with Cloud data.

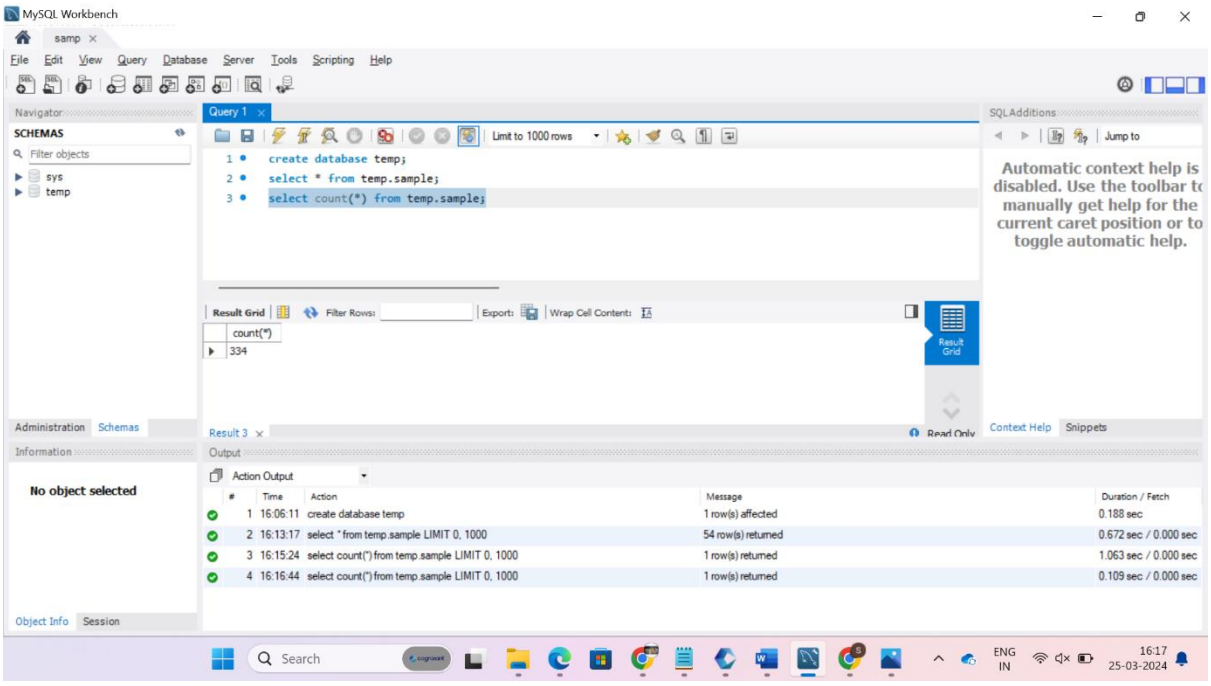



- Now the streaming is started. Now we will insert the file in data bricks as a steam process.

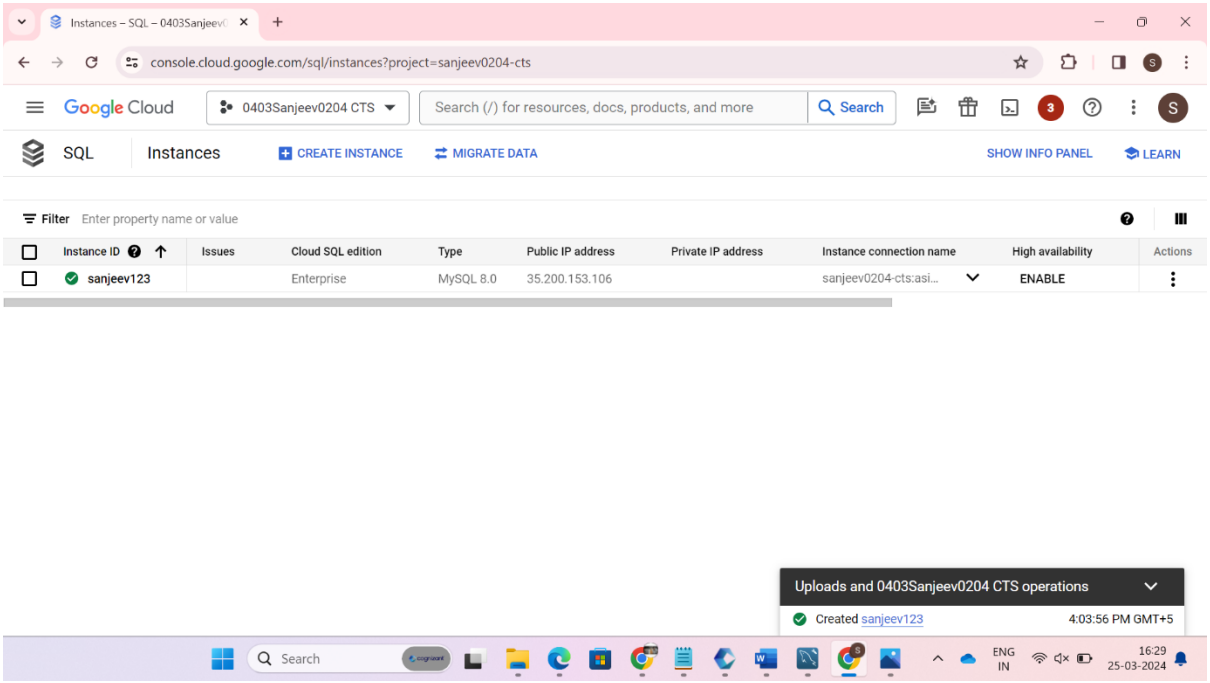





10) Now data will be stored in MySQL cloud. To get that data we need to open MySQL workbench and using select statement we can see that data.



11) before creating a instance in MySQL cloud.




# Conclusion:

Streaming and batch ETL are indispensable components of modern data processing architectures, offering organizations the flexibility to process data in real-time and batch modes according to their specific use cases and requirements. By leveraging both methodologies, organizations can derive actionable insights, optimize decision-making processes, and unlock new opportunities for innovation and growth in today's data-driven landscape.