

Data Processing Pipeline with Azure Data Factory

Table of Contents

- Project Statement
- Project Overview
- Prerequisites
- Azure Resources Used for the Project
- Project Objectives
- Tools Used
- Execution Overview
- Implementation-Tasks Performed
- Practical Implementation on Azure Portal
- Successful Output Generated
- Strategies for Implementing a Serverless Data Processing Pipeline with Azure Data Factory and Azure Databricks
- Conclusion

Project Statement:

Implement a serverless data processing pipeline where Azure Data Factory orchestrates data workflows, and Azure Databricks is used as a serverless processing engine for on-demand analytics and transformations.

Project Overview:

This project implements a comprehensive healthcare data analytics solution on Microsoft Azure. The pipeline processes raw healthcare data including patient information, doctor details, appointments, medical procedures, and billing records. The solution transforms this data into actionable insights through a multi-layered architecture that includes data ingestion, processing, transformation, and analytical reporting.

The system leverages Azure Data Factory for workflow orchestration and Azure Databricks as the serverless processing engine, creating an end-to-end serverless data pipeline that enables healthcare organizations to gain valuable insights into patient behavior, doctor performance, and operational efficiency.

Prerequisites:

1. **Azure Subscription:** Have an active Azure subscription for resource management.
2. **Azure Data Factory:** Create an Azure Data Factory instance.
3. **Azure Databricks:** Set up an Azure Databricks workspace for Spark processing.
4. **Azure Storage Account:** Create a storage account for CSV and Parquet files.
5. **Data Source:** Ensure the availability of the CSV file.
6. **Azure Access Key:** Obtain the Azure Access Key for the storage access.
7. **Access Permissions:** Grant ADF permissions for storage access.
8. **Databricks Cluster:** Set up a Databricks cluster for Spark jobs.
9. **Libraries and Dependencies:** Install required libraries in both ADF and Databricks.
10. **Monitoring and Logging:** Set up monitoring in ADF and Databricks.

Azure Resources Used for this Project:

- Azure Blob Storage
- Azure Data Factory
- Azure Storage Account
- Databricks Notebook Activity
- Azure Delta Tables

Project Objectives:

- Establish automated healthcare data pipelines using Azure Data Factory.
- Convert raw CSV healthcare data into optimized Parquet format.
- Implement multi-layered data architecture (Raw → Processed → Analyzed).
- Perform comprehensive data transformations and quality checks.
- Generate actionable healthcare insights through advanced analytics.
- Optimize data processing performance using partitioning and compression techniques.
- Create maintainable and documented data processing workflows.

Tools Used:

- **Azure Data Factory (Orchestration):** Pipeline management and workflow coordination.
- **Azure Databricks (Transformation Engine):** PySpark-based data processing.
- **Azure Blob Storage (Data Storage):** Multi-container architecture for different data layers.
- **Delta Lake Format:** For optimized storage and query performance.
- **PySpark Libraries:** Data transformation, analysis, and optimization.
- **SQL Analytics:** Business intelligence and reporting queries.

Execution Overview:

1. Data Storage Architecture

- **Raw:** CSV healthcare data stored in Azure Blob (raw container).
- **Source:** Cleaned & Processed Parquet files stored in source container.
- **Destination:** Transformed results are stored in the destination container for reporting.

2. Orchestration with Azure Data Factory

- **Three Separate Pipelines:** Ingestion, Transformation, and Analysis were created individually.
- **Master Pipeline:** These pipelines are combined using Execute Pipeline activity for end-to-end orchestration.
- **Linked Services:** ADF securely connects to Azure Databricks and Blob Storage.
- **Execution Flow:** Pipelines run sequentially with dependency management.
- **Monitoring & Logging:** Execution status, performance, and errors are tracked for all runs.

3. Data Processing in Azure Databricks:

Notebook Execution: Multiple Python notebooks are executed within Databricks workspace:

- **Data Ingestion Notebooks:** Read CSV files from the raw container, perform data cleaning, validation, and store as Parquet files in the source container.
- **Data Transformation Notebooks:** Read processed data from the source container, apply business logic transformation, and store final results in the destination container.
- **Data Writing:** Store cleaned data as Parquet files in the source container and final transformed results in the destination container.

4. Scheduling and Monitoring

- **Pipeline Execution:** Pipelines are triggered manually.
- **Monitoring:** ADF and Databricks dashboards track execution status and performance.
- **Error Handling:** Retry and alert mechanisms ensure reliability.
- **Optimization:** Performance is reviewed to identify improvements.

Implementation-Tasks Performed:

1. Define Data Sources and Storage Architecture

- Identified healthcare CSV files (patients, doctors, appointments, procedures, billing) stored in the raw container of Azure Blob Storage.
- Designed a multi-layer storage model:

- Source container has cleaned & processed Parquet files.
- Destination container has final transformed datasets.
- Defined clear directory structures within containers for better organization.

2. Set Up Azure Data Factory (ADF)

- Built three separate pipelines:
 - **Ingestion:** Process raw CSV and store them as Parquet in source container.
 - **Transformation:** Perform aggregations and apply transformation functions, then store the final transformed data in the destination container.
 - **Analysis:** Run analytical SQL queries on the transformed data.
- Combined them into a master pipeline using Execute Pipeline activity.
- Configured linked services for Blob Storage, Databricks and access keys.
- Implemented dependency management to ensure correct execution order.

3. Develop Databricks Notebooks

- **Ingestion notebooks:**
 - Read raw healthcare CSV files (patients, doctors, appointments, billing, medical procedures) from the raw container, applied cleaning (standardization, formatting, text normalization), validation (null checks, schema enforcement), deduplication, and added audit columns like ingestion timestamp.
 - Saved the processed datasets in both Delta tables (healthcare_processed) for query optimization and Parquet format in the source container, partitioned where relevant (e.g., appointments by year).
- **Transformation notebooks:**
 - Applied business logic by joining patients, doctors, appointments, billing, and procedures, and created insights such as day type, day bucket, first appointment flag, revenue trends, specialization demand, workload classification, and doctor rankings.
 - Stored the curated datasets (patient_appointment_summary, specialization_summary) in the destination container as Parquet and Delta tables for further analysis and reporting.

- **Analysis notebooks:**

- Developed SQL-based analytical notebooks in Databricks on top of curated Delta/Parquet datasets. Generated key aggregations such as appointment distribution by day/week/month, first-time vs. returning patients, payment analysis for top patients, and demand trends across medical specializations.
- Produced business insights including top-earning doctors, specialization workload and revenue ranking, and demand categorization. Final analytical results were structured and prepared for reporting and downstream decision-making.

4. Optimization & Monitoring

- **Performance tuning:** Optimized Spark queries, memory usage, and cluster configs for efficiency.
- **Monitoring:** Used ADF and Databricks dashboards to track execution times, resource usage, and detect failures.
- **Error handling:** Added retry & alert mechanisms.

Practical Implementation on Azure Portal

Step 1: Set Up Azure Databricks

[Home](#) > [rg-azuser4031_mm1local-yVJeu](#) > [Marketplace](#) > [Azure Databricks](#) >

Create an Azure Databricks workspace ...

×

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Project Details

Select the subscription to manage deployed resources and costs. Use resource groups like folders to organize and manage all your resources.

Subscription *	<input type="text" value="MML Learners"/>
Resource group *	<input type="text" value="rg-azuser4031_mm1local-yVJeu"/> Create new

Instance Details

Workspace name *	<input type="text" value="adfworkspace"/>
Region *	<input type="text" value="Central India"/>
Pricing Tier *	<input type="text" value="Standard (Apache Spark, Secure with Microsoft Entra ID)"/>
Managed Resource Group name	<input type="text" value="Enter name for managed resource group"/>

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Microsoft Azure

Search resources, services, and docs (G+/I)

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Deployment

rg-azuser4031_mml.local-yVJeu_adfworkspace01 | Overview

Search

Delete Cancel Redeploy Download Refresh

Overview

- Inputs
- Outputs
- Template

✓ Your deployment is complete

Deployment name : rg-azuser4031_mml.local-yVJeu_adfworkspace01 Start time : 8/25/2025, 2:26:55 PM
Subscription : MML Learners Correlation ID : f944900-43bb-4bd2-af9e-7989302f8f96
Resource group : rg-azuser4031_mml.local-yVJeu

> Deployment details

✓ Next steps

[Go to resource](#)

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Deployment succeeded

Deployment 'rg-azuser4031_mml.local-yVJeu_adfworkspace01' to resource group 'rg-azuser4031_mml.local-yVJeu' was successful.

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adfworkspace01

Azure Databricks Service

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Overview

- Activity log
- Access control (IAM)
- Tags
- Diagnose and solve problems
- Resource visualizer
- Settings
- Automation
- Help

Essentials

Status : Active
Resource group : rg-azuser4031_mml.local-yVJeu
Location : Central India
Subscription : MML Learners
Subscription ID : 2a3c6418-97b9-4d96-a24b-2c2d7633d375
Tags (edit) : [Add tags](#)

Managed Resource Group : databricks-rg-adfworkspace01-hcspgwm47o6
URL : <https://adb-32355871479287499.azure.databricks.net>
Pricing Tier : Standard (Apache Spark - Secure with Microsoft Entra ID) (Click to c...
Enable No Public IP : Yes

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Create a Databricks workspace and a cluster in the Azure Portal.

Microsoft Azure databricks

Search data, notebooks, recent, and more...

CTRL + P

adfworkspace01

New

- Workspace
- Recents
- Catalog
- Jobs & Pipelines
- Compute**
- Data Engineering
- Job Runs
- AI/ML
- Playground
- Experiments
- Features
- Models
- Serving

Compute > New compute > Simple form: ON

Create new compute

General

Compute name : adf-project-cluster

Policy : Unrestricted

Performance

☐ Machine learning ☒

Databricks runtime : 14.3 LTS Scala 2.12, Spark 3.5.0 ☐ Photon acceleration

Node type : Standard_DS3_v2 14 GB Memory, 4 Cores ☒ Single node

☒ Terminate after 30 minutes of inactivity

Advanced performance

Tags

Key Value

[Create](#) [Cancel](#)

Summary

14 GB Memory, 4 Cores

Data access

-

Price

0.75 DBU/h

Step -2 Creating Azure Storage Account

Create an Azure Storage Account to store our files.

[Home](#) > [rg-azuser4031_mml.local-yVJeu](#) > [Marketplace](#) > [Storage account](#) >

Create a storage account

Project details

Select the subscription in which to create the new storage account. Choose a new or existing resource group to organize and manage your storage account together with other resources.

Subscription *

Resource group *
[Create new](#)

Instance details

Storage account name *

Region *
[Deploy to an Azure Extended Zone](#)

Primary service

Performance * ☒ **Standard:** Recommended for most scenarios (general-purpose v2 account)
☐ **Premium:** Recommended for scenarios that require low latency.

Redundancy *

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projectadf_1756111703361 | Overview

Deployment

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Overview

- Inputs
- Outputs
- Template

Your deployment is complete

Deployment name: projectadf_1756111703361
Subscription: MML Learners
Resource group: rg-azuser4031_mml.local-yVJeu

Start time: 8/25/2025, 2:20:38 PM
Correlation ID: 0927a5d1-a24b-4913-8b1c-b361f263a4c6

Deployment details

Resource	Type	Status	Operation details
projectadf/default	Microsoft.Storage/storageAccount...	OK	Operation details
projectadf/default	Microsoft.Storage/storageAccount...	OK	Operation details
projectadf	Microsoft.Storage/storageAccounts	OK	Operation details

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Create three containers

- Raw container holds the csv files
- Source container holds the cleaned and processed data
- Destination container holds the transformed data

Microsoft Azure portal interface showing the 'Containers' section of a storage account named 'projectadf'. The left sidebar lists navigation options: Overview, Activity log, Tags, Diagnose and solve problems, Access Control (IAM), Data migration, Events, Storage browser, Partner solutions, Resource visualizer, Data storage, Containers, File shares, Queues, Tables, Security + networking, and Data management. The main area displays a table of containers:

Name	Last modified	Anonymous access level	Lease state
\$logs	8/25/2025, 2:23:11 PM	Private	Available
destination	8/25/2025, 2:28:11 PM	Private	Available
raw	8/25/2025, 2:27:55 PM	Private	Available
source	8/25/2025, 2:28:03 PM	Private	Available

The right sidebar shows a 'Notifications' panel with three messages:

- Successfully created storage container 'destination'.
- Successfully created storage container 'source'.
- Successfully created storage container 'raw'.

Uploading csv to the raw container

We used [Healthcare Management System dataset](#) from kaggle

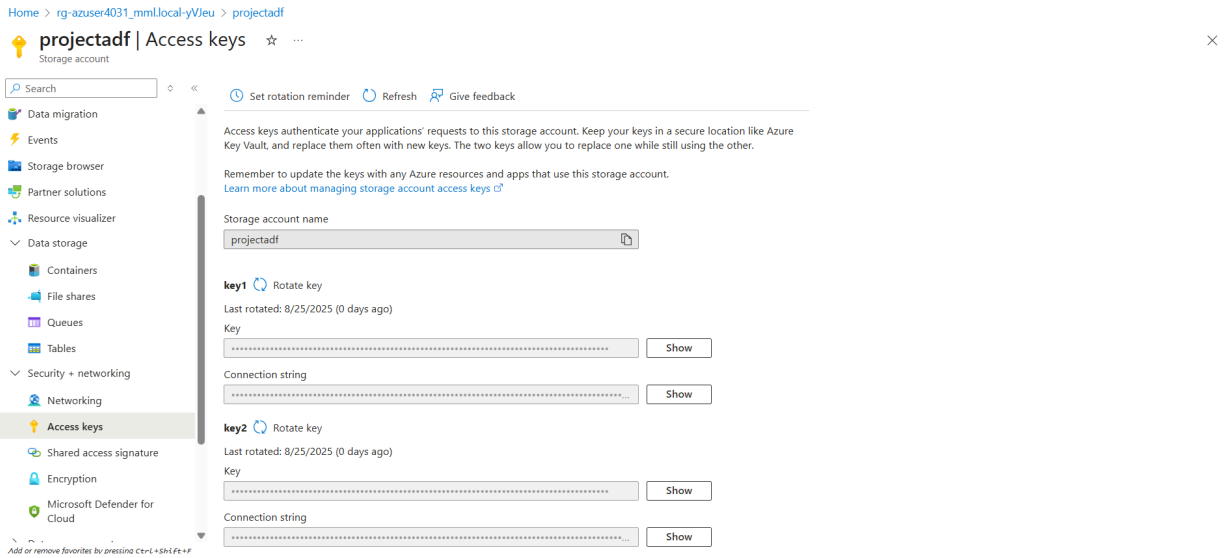
Microsoft Azure portal interface showing the 'raw' container of the 'projectadf' storage account. The left sidebar lists navigation options: Overview, Diagnose and solve problems, Access Control (IAM), and Settings. The main area displays a table of blobs in the 'raw' container:

Name	Last modified	Access tier	Blob type	Size
Appointment...	8/25/2025, 2:29:05 PM	Hot (Inferred)	Block blob	47.89 KiB
Billing.csv	8/25/2025, 2:29:05 PM	Hot (Inferred)	Block blob	70.58 KiB
Doctor.csv	8/25/2025, 2:29:05 PM	Hot (Inferred)	Block blob	39.75 KiB
Medical_Pr...	8/25/2025, 2:29:05 PM	Hot (Inferred)	Block blob	31.9 KiB
Patient.csv	8/25/2025, 2:29:05 PM	Hot (Inferred)	Block blob	44.65 KiB

The right sidebar shows a 'Notifications' panel with one message:

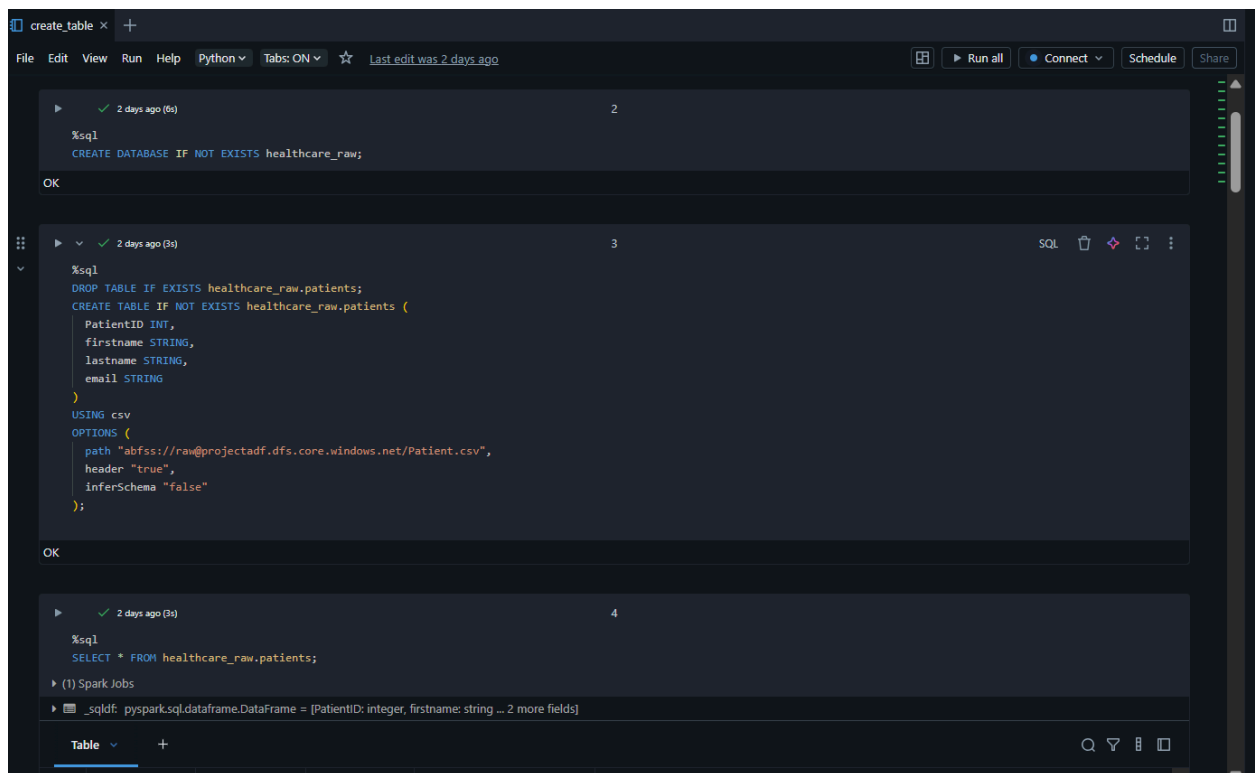
- Successfully uploaded blob(s).

Get Access Key from Storage account to access the containers we have created



In the DataBricks WorkSpace, Create a new Notebook for creating the table for all the csv files we have in the raw container.

tables/create_table



create_table × +

File Edit View Run Help Python ▾ Tabs: ON ☆ Last edit was 2 days ago

Run all Connect Schedule Share

2 days ago (1s) 7

```
%sql
DROP TABLE IF EXISTS healthcare_raw.appointments;
CREATE TABLE IF NOT EXISTS healthcare_raw.appointments (
  AppointmentID INT,
  Date DATE,
  Time STRING,
  PatientID INT,
  DoctorID INT
)
USING csv
OPTIONS (
  path "abfss://raw@projectadf.dfs.core.windows.net/Appointment.csv",
  header "true",
  inferSchema "false"
);
```

OK

2 days ago (1s) 8

```
%sql
SELECT * FROM healthcare_raw.appointments;
```

(1) Spark Jobs

```
_sqldf: pyspark.sql.dataframe.DataFrame = [AppointmentID: integer, Date: date ... 3 more fields]
```

Table +

	AppointmentID	Date	Time	PatientID	DoctorID
1	639	2022-04-08	2023-12-23T14:33:46.40...	109	462
2	404	2023-04-10	2023-12-23T14:33:46.40...	823	774
3	281	2022-12-09	2023-12-23T14:33:46.40...	465	226

create_table × +

File Edit View Run Help Python ▾ Tabs: ON ☆ Last edit was 2 days ago

Run all Connect Schedule Share

2 days ago (1s) 9

```
%sql
DROP TABLE IF EXISTS healthcare_raw.medical_procedure;
CREATE TABLE IF NOT EXISTS healthcare_raw.medical_procedure (
  ProcedureID INT,
  ProcedureName STRING,
  AppointmentID INT
)
USING csv
OPTIONS (
  path "abfss://raw@projectadf.dfs.core.windows.net/Medical_Procedure.csv",
  header "true",
  inferSchema "false"
);
```

OK

2 days ago (1s) 10

```
%sql
SELECT * FROM healthcare_raw.medical_procedure;
```

(1) Spark Jobs

```
_sqldf: pyspark.sql.dataframe.DataFrame = [ProcedureID: integer, ProcedureName: string ... 1 more field]
```

Table +

	ProcedureID	ProcedureName	AppointmentID
1	432	Kidney transplant	955
2	574	Allergy testing	701
3	854	Psychotherapy	363
4	818	Emotional and spiritual support	959
5	672	Hormone replacement therapy	439
6	869	Coronary artery bypass surgery	805

create_table x +

File Edit View Run Help Python Tabs: ON ☆ Last edit was 2 days ago

Run all Connect Schedule Sha

2 days ago (1s) 11

```
%sql
DROP TABLE IF EXISTS healthcare_raw.billing;
CREATE TABLE IF NOT EXISTS healthcare_raw.billing (
  InvoiceID INT,
  PatientID INT,
  Items STRING,
  Amount DOUBLE
)
USING csv
OPTIONS (
  path "abfss://raw@projectadf.dfs.core.windows.net/Billing.csv",
  header "true",
  inferSchema "false"
);
```

OK

2 days ago (<1s) 12

```
%sql
SELECT * FROM healthcare_raw.billing;
```

(1) Spark Jobs

```
_sqldf: pyspark.sql.dataframe.DataFrame = [InvoiceID: integer, PatientID: integer ... 2 more fields]
```

Table +

InvoiceID PatientID Items Amount

1 null 894 Immunizations 956065

2 null 448 Cataract surgery 188997

3 null 618 Pediatric surgery 524091

4 null 117 Rhinoplasty 901393

5 null 374 Antibiotic therapy 448957

Create 5 more notebooks called ingest_patients, ingest_billing, ingest_appointments, ingest_medical_procedure, ingest_doctor for ingesting the data to the source container.

ingestion/ingest_patient

2 days ago (1s) 2

```
from pyspark.sql.types import StructType, Structfield, IntegerType, StringType
from pyspark.sql.functions import col, concat, lit, current_timestamp

# Read from the raw table we created
patients_raw_df = spark.read.table("healthcare_raw.patients")
```

patients_raw_df: pyspark.sql.dataframe.DataFrame = [PatientID: integer, firstname: string ... 2 more fields]

2 days ago (<1s) 3

```
from pyspark.sql.functions import lower

patients_cleaned_df = (patients_raw_df
    .withColumn("full_name", concat(col("firstname"), lit(" "), col("lastname"))) # Create full name
    .withColumn("email", lower(col("email"))) # Standardize email to lowercase
    .dropDuplicates(["PatientID"]) # Remove duplicate patients
    .withColumn("ingestion_date", current_timestamp()) # Add audit timestamp
    .select(
        col("PatientID").alias("patient_id"),
        "full_name",
        "email",
        "ingestion_date"
    )
)
```

patients_cleaned_df: pyspark.sql.dataframe.DataFrame = [patient_id: integer, full_name: string ... 2 more fields]

2 days ago (<1s) 4

```
spark.sql("CREATE DATABASE IF NOT EXISTS healthcare_processed")
```

2 days ago (17h) 5

```
patients_cleaned_df.write.mode("overwrite").format("delta").saveAsTable("healthcare_processed.patients")

patients_cleaned_df.write.mode("overwrite").parquet(f"abfss://source/projectadf.dfs.core.windows.net/patients")
```

(9) Spark Jobs

2 days ago (2h) 6 Python

```
display(spark.read.table("healthcare_processed.patients"))
print("Patients ingestion completed successfully!")
```

(2) Spark Jobs

Table +

	patient_id	full_name	email	ingestion_date
1	101	Ira Eachern	ira.eachern@yopmail.com	2025-08-25T09:23:19.083+00:...
2	103	Lusa Alisia	lusa.alisia@yopmail.com	2025-08-25T09:23:19.083+00:...
3	104	Joane Yam	joane.yam@yopmail.com	2025-08-25T09:23:19.083+00:...
4	106	Petronia Tamsky	petronia.tamsky@yopmail.com	2025-08-25T09:23:19.083+00:...
5	108	Antonietta Claudine	antonietta.claudine@yopmail.com	2025-08-25T09:23:19.083+00:...
6	111	Leontine Zachary	leontine.zachary@yopmail.com	2025-08-25T09:23:19.083+00:...
7	112	Elbertina Dosia	elbertina.dosia@yopmail.com	2025-08-25T09:23:19.083+00:...
8	115	Blondelle Riordan	blondelle.riordan@yopmail.com	2025-08-25T09:23:19.083+00:...
9	116	Babita Felecia	babita.felecia@yopmail.com	2025-08-25T09:23:19.083+00:...

ingestion/ingest_doctor

2 days ago (<1h) 2

```
from pyspark.sql.functions import col, trim, lower, initcap, current_timestamp
from pyspark.sql.types import StructType, StructField, IntegerType, StringType

doctors_raw_df = spark.read.table("healthcare_raw.doctors")
```

doctors_raw_df: pyspark.sql.dataframe.DataFrame = [DoctorID: integer, DoctorName: string ... 2 more fields]

2 days ago (<1h) 3 Python

```
doctors_cleaned_df = (doctors_raw_df
    # Clean text fields
    .withColumn("doctor_name", trim(initcap(col("DoctorName")))) # Capitalize first letters and trim
    .withColumn("specialization", trim(lower(col("Specialization")))) # Standardize to lowercase
    .withColumn("contact_info", trim(col("DoctorContact")))

    # Data quality: Remove doctors without name or specialization
    .filter(col("DoctorName").isNotNull() & col("Specialization").isNotNull())

    # Remove duplicates
    .dropDuplicates(["DoctorID"])

    # Add audit columns
    .withColumn("ingestion_date", current_timestamp())

    # Select and rename final columns
    .select(
        col("DoctorID").alias("doctor_id"),
        "doctor_name",
        "specialization",
        "contact_info",
        "ingestion_date"
    )
)
```

2 days ago (5s) 4

```
doctors_cleaned_df.write.mode("overwrite").format("delta").saveAsTable("healthcare_processed.doctors")

doctors_cleaned_df.write.mode("overwrite").parquet(f"abfss://source@projectadf.dfs.core.windows.net/doctors")
```

▶ (9) Spark Jobs

2 days ago (1s) 5

```
print("Total doctors processed:", doctors_cleaned_df.count())
display(doctors_cleaned_df.limit(5))
```

▶ (5) Spark Jobs

Total doctors processed: 600

	doctor_id	doctor_name	specialization	contact_info	ingestion_date
1	100	Thalia	emergency medicine	.@yopmail.com	2025-08-25T09:25:29.365+00...
2	101	Mireielle	allergists	.@yopmail.com	2025-08-25T09:25:29.365+00...
3	103	Eile	endocrinologist	.@yopmail.com	2025-08-25T09:25:29.365+00...
4	104	Cacile	emergency medicine	.@yopmail.com	2025-08-25T09:25:29.365+00...
5	105	Lynae	emergency medicine	.@yopmail.com	2025-08-25T09:25:29.365+00...

ingest/ingest_appointment

2 days ago (<1s) 2

```
from pyspark.sql.functions import col, to_timestamp, concat, date_format, current_timestamp
appointments_raw_df = spark.read.table("healthcare_raw.appointments")
```

appointments_raw_df: pyspark.sql.dataframe.DataFrame = [AppointmentID: integer, Date: date ... 3 more fields]

2 days ago (<1s) 3

```
from pyspark.sql.functions import col, to_date, to_timestamp, date_format, dayofmonth, current_timestamp

appointments_cleaned_df = (appointments_raw_df
    # Keep Date column as is (string from CSV)
    .withColumn("appointment_date", col("Date"))

    # Convert to proper date for extracting parts
    .withColumn("date_parsed", to_date(col("Date"), "dd-MM-yyyy"))

    # Extract year, month, and day
    .withColumn("appointment_year", date_format(col("date_parsed"), "yyyy"))
    .withColumn("appointment_month", date_format(col("date_parsed"), "MM"))
    .withColumn("appointment_day", dayofmonth(col("date_parsed")))

    # Parse Time column (ISO timestamp)
    .withColumn("appointment_timestamp", to_timestamp(col("Time"), "yyyy-MM-dd'T'HH:mm:ss.SSS'Z'"))

    # Add ingestion timestamp
    .withColumn("ingestion_date", current_timestamp())

    # Deduplicate
    .dropDuplicates(["AppointmentID"])

    # Final selection
    .select(
        col("AppointmentID").alias("appointment_id"),
        "appointment_timestamp",
        "appointment_date",      # original string from CSV
        "appointment_year",
        "appointment_month",
        "appointment_day",      # new day column (int 1-31)
        col("patientID").alias("patient_id"),
        col("doctorID").alias("doctor_id"),
        "ingestion_date"
    )
)
```

2 days ago (1s)

4

```
(appointments_cleaned_df.write
    .mode("overwrite")
    .format("delta")
    .partitionBy("appointment_year")
    .saveAsTable("healthcare_processed.appointment"))
```

(7) Spark Jobs

2 days ago (1s)

5

```
appointments_cleaned_df.printSchema()
```

root

```
 |-- appointment_id: integer (nullable = true)
 |-- appointment_timestamp: timestamp (nullable = true)
 |-- appointment_date: date (nullable = true)
 |-- appointment_year: string (nullable = true)
 |-- appointment_month: string (nullable = true)
 |-- appointment_day: integer (nullable = true)
 |-- patient_id: integer (nullable = true)
 |-- doctor_id: integer (nullable = true)
 |-- ingestion_date: timestamp (nullable = false)
```

2 days ago (1s)

6

```
appointments_cleaned_df.write.mode("overwrite").parquet(f"abfss://source@projectadf.dfs.core.windows.net/appointments")
```

(2) Spark Jobs

2 days ago (1s)

7

```
display(spark.read.table("healthcare_processed.appointment").limit(5))
print("Appointments ingestion completed successfully!")
```

(2) Spark Jobs

Table

+

	appointment_id	appointment_timestamp	appointment_date	appointment_year	appointment_month	appointment_day	patient_id	doctor_id	ingestion_date
1	105	2023-12-23T14:33:46.410+00:00	2020-01-29	2020	01	29	270	912	2025-08-25T09:28:06.146+00:...
2	109	2023-12-23T14:33:46.410+00:00	2020-11-08	2020	11	8	439	480	2025-08-25T09:28:06.146+00:...

ingestion/ingest_billing

2 days ago (1s)

2

```
from pyspark.sql.functions import col, trim, round, current_timestamp, when
from pyspark.sql.types import DoubleType

billing_raw_df = spark.read.table("healthcare_raw.billing")
```

billing_raw_df: pyspark.sql.dataframe.DataFrame = [InvoiceID: integer, PatientID: integer ... 2 more fields]

2 days ago (1s)

3

```
from pyspark.sql.functions import lower
billing_cleaned_df = (billing_raw_df.select(col("InvoiceID").alias("invoice_id"),
                                           col("PatientID").alias("patient_id"),
                                           col("Items").alias("items"),
                                           col("Amount").alias("amount")))
billing_cleaned_df.display()
```

(1) Spark Jobs

billing_cleaned_df: pyspark.sql.dataframe.DataFrame = [invoice_id: integer, patient_id: integer ... 2 more fields]

Table

+

	invoice_id	patient_id	items	amount
1		894	Immunizations	956065
2		448	Cataract surgery	188997
3		618	Pediatric surgery	524091
4		117	Rhinoplasty	901393
5		374	Antibiotic therapy	448957
6		852	Emergency surgical procedures	869041
7		834	Pediatric surgery	482022
8		140	Hemodynamic monitoring	644419
9		459	Emergency surgical procedures	295907

Step-3 : Create a Data Factory

Create a new Azure Data Factory for performing the file conversion.

2 days ago (4)

```

(billing_cleaned_df.write
 .mode("overwrite")
 .format("delta")
 .saveAsTable("healthcare_processed.billing"))

# write to cloud storage
billing_cleaned_df.write.mode("overwrite").parquet("abfss://source@projectadf.dfs.core.windows.net/billing")

```

(7) Spark Jobs

2 days ago (14)

```

from pyspark.sql.functions import sum, count, avg

summary_df = billing_cleaned_df.agg(
    count("*").alias("total_invoices"),
    sum("amount").alias("total_revenue"),
    round(avg("amount"), 2).alias("average_invoice_amount")
)

print("Billing Summary:")
display(summary_df)

```

(2) Spark Jobs

summary_df: pyspark.sql.dataframe.DataFrame = [total_invoices: long, total_revenue: double ... 1 more field]

Billing Summary:

	total_invoices	total_revenue	average_invoice_amount
1	1000	510275708	510275.71

ingestion/ingest_medical_procedure

2 days ago (14)

```

from pyspark.sql.functions import col, trim, lower, initcap, current_timestamp

procedures_raw_df = spark.read.table("healthcare_raw.medical_procedure")

```

procedures_raw_df: pyspark.sql.dataframe.DataFrame = [ProcedureID: integer, ProcedureName: string ... 1 more field]

2 days ago (14)

```

procedures_cleaned_df = (procedures_raw_df
    # Clean text fields
    .withColumn("procedure_name", trim(initcap(col("ProcedureName"))))

    # Data validation: Ensure required fields are present
    .filter(col("ProcedureName").isNotNull() & col("AppointmentID").isNotNull())

    # Remove duplicates (same procedure for same appointment shouldn't happen)
    .dropDuplicates(["ProcedureID", "AppointmentID"])

    # Add audit column
    .withColumn("ingestion_date", current_timestamp())

    # Select and rename final columns
    .select(
        col("ProcedureID").alias("procedure_id"),
        "procedure_name",
        col("AppointmentID").alias("appointment_id"),
        "ingestion_date"
    )
)

```

procedures_cleaned_df: pyspark.sql.dataframe.DataFrame = [procedure_id: integer, procedure_name: string ... 2 more fields]

2 days ago (54)

```

procedures_cleaned_df.write.mode("overwrite").format("delta").saveAsTable("healthcare_processed.medical_procedures")

# write to cloud storage
procedures_cleaned_df.write.mode("overwrite").parquet("abfss://source@projectadf.dfs.core.windows.net/medical_procedures")

```

(9) Spark Jobs

To perform transformation, inside transformation folder create two notebooks

transformation/patient_appointment_summary

Read Source Tables

```
2 days ago (1s) 3 Python

# Read appointments data
appointments_df = spark.read.format("parquet").load(f"abfss://source@projectadf.dfs.core.windows.net/appointments")
patients_df = spark.read.format("parquet").load(f"abfss://source@projectadf.dfs.core.windows.net/patients")
doctors_df = spark.read.format("parquet").load(f"abfss://source@projectadf.dfs.core.windows.net/doctors")
billing_df = spark.read.format("parquet").load(f"abfss://source@projectadf.dfs.core.windows.net/billing")
procedures_df = spark.read.format("parquet").load(f"abfss://source@projectadf.dfs.core.windows.net/medical_procedures")
```

(5) Spark Jobs

```
appointments_df: pyspark.sql.dataframe.DataFrame = [appointment_id: integer, appointment_timestamp: timestamp ... 7 more fields]
billing_df: pyspark.sql.dataframe.DataFrame = [invoice_id: integer, patient_id: integer ... 2 more fields]
doctors_df: pyspark.sql.dataframe.DataFrame = [doctor_id: integer, doctor_name: string ... 3 more fields]
patients_df: pyspark.sql.dataframe.DataFrame = [patient_id: integer, full_name: string ... 2 more fields]
procedures_df: pyspark.sql.dataframe.DataFrame = [procedure_id: integer, procedure_name: string ... 2 more fields]
```

Build Base Data (Joins)

```
2 days ago (1s) 5

billing_df.printSchema()
billing_df.show(20, truncate=False)
billing_df.select("patient_id").distinct().show()
```

(3) Spark Jobs

```
471|
496|
623|
858|
897|
243|
616|
```

```
2 days ago (1s) 6 Python

# Join appointments with patients
appointment_patient_df = appointments_df.join(
    patients_df,
    appointments_df.patient_id == patients_df.patient_id,
    "inner"
).select(
    appointments_df["*"],
    patients_df["full_name"].alias("patient_name"),
    patients_df["email"].alias("patient_email")
)

# Join with doctors
appointment_doctor_df = appointment_patient_df.join(
    doctors_df,
    appointment_patient_df.doctor_id == doctors_df.doctor_id,
    "inner"
).select(
    appointment_patient_df["*"],
    doctors_df["doctor_name"],
    doctors_df["specialization"],
    doctors_df["contact_info"].alias("doctor_contact")
)

# Join with procedures
appointment_procedure_df = appointment_doctor_df.join(
    procedures_df,
    appointment_doctor_df.appointment_id == procedures_df.appointment_id,
    "left"
).select(
    appointment_doctor_df["*"],
    procedures_df["procedure_name"],
    procedures_df["procedure_id"]
)

# Join with billing (aggregate billing by appointment)
from pyspark.sql.functions import sum, coalesce, lit

billing_agg_df = billing_df.groupBy("patient_id").agg(
    sum("amount").alias("total_amount"),
    sum(coalesce(col("amount"), lit(0))).alias("total_billing")
)

appointment_summary_base_df = appointment_procedure_df.join(
    billing_agg_df,
    appointment_procedure_df.patient_id == billing_agg_df.patient_id,
    "left"
).drop(billing_agg_df.patient_id)
```

Add Day Name (Text Format of Date)

2 days ago (2h) 8 Python

```
from pyspark.sql.functions import col, date_format

appointment_summary_df = appointment_summary_base_df.withColumn(
    "day_name", date_format(col("appointment_date"), "EEEE")
)
appointment_summary_df.display()
```

(6) Spark Jobs

appointment_summary_df: pyspark.sql.dataframe.DataFrame = [appointment_id: integer, appointment_timestamp: timestamp ... 17 more fields]

	appointment_id	appointment_timestamp	appointment_date	appointment_year	appointment_month	appointment_day	patient_id	doctor_id	ingestion_date	
1	531	2023-12-23T14:33:46.412+00:00	2022-06-13	2022	06	13	103	291	2025-08-25T09:28:10.877+00...	Lus
2	455	2023-12-23T14:33:46.410+00:00	2023-03-15	2023	03	15	103	388	2025-08-25T09:28:10.877+00...	Lus
3	656	2023-12-23T14:33:46.414+00:00	2023-07-25	2023	07	25	112	612	2025-08-25T09:28:10.877+00...	Elbr

First Appointment Flag

2 days ago (1h) 10 Python

```
from pyspark.sql import Window
from pyspark.sql.functions import row_number, when, col
# Transformation 3: Flag is_first_appointment for each patient
# Create window specification by patient_id ordered by appointment timestamp
patient_window = Window.partitionBy("patient_id").orderBy("appointment_timestamp")

appointment_summary_df = appointment_summary_df.withColumn(
    "appointment_rank",
    row_number().over(patient_window)
).withColumn(
    "is_first_appointment",
    when(col("appointment_rank") == 1, True).otherwise(False)
).drop("appointment_rank")
appointment_summary_df.display()
```

(7) Spark Jobs

appointment_summary_df: pyspark.sql.dataframe.DataFrame = [appointment_id: integer, appointment_timestamp: timestamp ... 18 more fields]

	appointment_id	appointment_timestamp	appointment_date	appointment_year	appointment_month	appointment_day	patient_id	doctor_id	ingestion_date	
1	455	2023-12-23T14:33:46.410+00:00	2023-03-15	2023	03	15	103	388	2025-08-25T09:28:10.877+00...	Lus
2	531	2023-12-23T14:33:46.412+00:00	2022-06-13	2022	06	13	103	291	2025-08-25T09:28:10.877+00...	Lus
3	443	2023-12-23T14:33:46.408+00:00	2022-11-27	2022	11	27	112	210	2025-08-25T09:28:10.877+00...	Elbr
4	619	2023-12-23T14:33:46.412+00:00	2022-06-16	2022	06	16	112	926	2025-08-25T09:28:10.877+00...	Elbr

Day Bucket (Early / Mid / Late Month)

2 days ago (1h) 12 Python

```
from pyspark.sql.functions import dayofmonth

appointment_summary_df = appointment_summary_df.withColumn(
    "appointment_day_num", dayofmonth("appointment_date")
).withColumn(
    "day_bucket",
    when(col("appointment_day_num") <= 10, "Early Month")
    .when((col("appointment_day_num") > 10) & (col("appointment_day_num") <= 20), "Mid Month")
    .otherwise("Late Month")
)
appointment_summary_df.display()
```

(7) Spark Jobs

appointment_summary_df: pyspark.sql.dataframe.DataFrame = [appointment_id: integer, appointment_timestamp: timestamp ... 20 more fields]

	appointment_id	appointment_timestamp	appointment_date	appointment_year	appointment_month	appointment_day	patient_id	doctor_id	ingestion_date	
1	455	2023-12-23T14:33:46.410+00:00	2023-03-15	2023	03	15	103	388	2025-08-25T09:28:10.877+00...	Lus
2	531	2023-12-23T14:33:46.412+00:00	2022-06-13	2022	06	13	103	291	2025-08-25T09:28:10.877+00...	Lus
3	443	2023-12-23T14:33:46.408+00:00	2022-11-27	2022	11	27	112	210	2025-08-25T09:28:10.877+00...	Elbr

Day Type (Weekday vs Weekend)

```
from pyspark.sql.functions import dayofweek

appointment_summary_df = appointment_summary_df.withColumn(
    "day_of_week_num", dayofweek("appointment_date")
).withColumn(
    "day_type",
    when((col("day_of_week_num") == 1) | (col("day_of_week_num") == 7), "Weekend")
    .otherwise("Weekday")
)
appointment_summary_df.display()
```

(7) Spark Jobs

appointment_summary_df: pyspark.sql.dataframe.DataFrame = [appointment_id: integer, appointment_timestamp: timestamp ... 22 more fields]

	appointment_id	appointment_timestamp	appointment_date	appointment_year	appointment_month	appointment_day	patient_id	doctor_id	ingestion_date		
1	455	2023-12-23T14:33:46.410+00:00	2023-03-15	2023	03		15	103	388	2025-08-25T09:28:10.877+00...	Lus
2	531	2023-12-23T14:33:46.412+00:00	2022-06-13	2022	06		13	103	291	2025-08-25T09:28:10.877+00...	Lus
3	443	2023-12-23T14:33:46.408+00:00	2022-11-27	2022	11		27	112	210	2025-08-25T09:28:10.877+00...	Elbi

```
# Build the final curated DataFrame
final_summary_df = appointment_summary_df.select(
    "appointment_id",
    "appointment_timestamp",
    "appointment_date",
    "appointment_year",
    "appointment_month",
    "appointment_day",
    "patient_id",
    "patient_name",
    "patient_email",
    "doctor_id",
    "doctor_name",
    "specialization",
    "doctor_contact",
    "procedure_id",
    "procedure_name",
    "total_amount",
    "day_name",
    "appointment_day_num",
    "day_bucket",
    "day_of_week_num",
    "day_type",
    "is_first_appointment",
    "ingestion_date"
)

# Preview
final_summary_df.display()
```

(7) Spark Jobs

final_summary_df: pyspark.sql.dataframe.DataFrame = [appointment_id: integer, appointment_timestamp: timestamp ... 20 more fields]

	appointment_id	appointment_timestamp	appointment_date	appointment_year	appointment_month	patient_id	patient_name	patient_email	doctor_id	
15	860	2023-12-23T14:33:46.416+00:00	2023-08-30	2023	08	131	Jaclyn Euridice	jaclyn.euridice@yopmail.com	944	Elena
16	464	2023-12-23T14:33:46.408+00:00	2023-04-29	2023	04	133	Mariele Emanuel	mariele.emmanuel@yopmail.com	505	Jobi
17	464	2023-12-23T14:33:46.408+00:00	2023-04-29	2023	04	133	Mariele Emanuel	mariele.emmanuel@yopmail.com	505	Jobi

```
%sql
create database if not exists healthcare_analysis;

OK
```

(2 days ago (16))

```
final_summary_df.write.mode("overwrite").format("delta").saveAsTable(
    "healthcare_analysis.patient_appointment_summary"
)
```

(12) Spark Jobs

(2 days ago (18))

```
final_summary_df.write.mode("overwrite").parquet(
    f"abfss://destination@projectadfs.core.windows.net/patient_appointment_summary"
)
```

(7) Spark Jobs

Transformation/specialization_summary

Read required processed data

```
appointments_df = spark.read.format("parquet").load("abfss://source@projectadf.dfs.core.windows.net/appointments")
doctors_df = spark.read.format("parquet").load("abfss://source@projectadf.dfs.core.windows.net/doctors")
billing_df = spark.read.format("parquet").load("abfss://source@projectadf.dfs.core.windows.net/billing")
```

▶ (3) Spark Jobs

appointments_df: pyspark.sql.dataframe.DataFrame = [appointment_id: integer, appointment_timestamp: timestamp ... 7 more fields]

billing_df: pyspark.sql.dataframe.DataFrame = [invoice_id: integer, patient_id: integer ... 2 more fields]

doctors_df: pyspark.sql.dataframe.DataFrame = [doctor_id: integer, doctor_name: string ... 3 more fields]

Transformation 1: Number of doctors in each specialization

```
# Transformation 1: Number of doctors in each specialization
from pyspark.sql.functions import count
doctors_per_specialization = doctors_df.groupBy("specialization").agg(
    count("doctor_id").alias("number_of_doctors")
)
print("Number of doctors per specialization:")
doctors_per_specialization.show()
```

▶ (2) Spark Jobs

doctors_per_specialization: pyspark.sql.dataframe.DataFrame = [specialization: string, number_of_doctors: long]

specialization	number_of_doctors
geriatrician	20
gastroenterology	33

Transformation 2: Revenue per year by doctor and specialization

```
from pyspark.sql.functions import sum, col

# Join billing with appointments using patient_id to get doctor_id and year, then with doctors for specialization
revenue_by_doctor_year = billing_df.join(
    appointments_df.select("patient_id", "doctor_id", "appointment_year"),
    "patient_id",
    "inner"
).join(
    doctors_df.select("doctor_id", "doctor_name", "specialization"),
    "doctor_id",
    "inner"
).groupBy("doctor_id", "doctor_name", "specialization", "appointment_year").agg(
    sum("amount").alias("yearly_revenue")
)

print("Revenue by doctor and year:")
revenue_by_doctor_year.orderBy("appointment_year", "yearly_revenue", ascending=False).show()
```

▶ (4) Spark Jobs

revenue_by_doctor_year: pyspark.sql.dataframe.DataFrame = [doctor_id: integer, doctor_name: string ... 3 more fields]

Revenue by doctor and year:

doctor_id	doctor_name	specialization	appointment_year	yearly_revenue
667	Gloria	geriatrician	2023	4035149.0
801	Brooks	dermatology	2023	3436703.0
452	Minne	critical care med...	2023	3436703.0
189	Max	family medicine	2023	3283643.0

Transformation 3: Total revenue for each doctor by year

```
total_revenue_by_doctor_year = revenue_by_doctor_year.groupBy("doctor_id", "doctor_name", "specialization", "appointment_year").agg(
    sum("yearly_revenue").alias("total_yearly_revenue")
)

print("Total revenue per doctor by year:")
total_revenue_by_doctor_year.orderBy("appointment_year", "total_yearly_revenue", ascending=False).show()
```

▶ (4) Spark Jobs

total_revenue_by_doctor_year: pyspark.sql.dataframe.DataFrame = [doctor_id: integer, doctor_name: string ... 3 more fields]

Total revenue per doctor by year:

doctor_id	doctor_name	specialization	appointment_year	total_yearly_revenue
667	Gloria	geriatrician	2023	4035149.0
801	Brooks	dermatology	2023	3436703.0
452	Minne	critical care med...	2023	3436703.0
189	Max	family medicine	2023	3283643.0

Transformation 4: Yearly specialization count for each year

```
from pyspark.sql.functions import col, count

# Ensure year is integer
appointments_clean = appointments_df.withColumn(
    "year_int", col("appointment_year").cast("int")
)

# Join with doctors to bring specialization info
yearly_specialization_appointments = (
    appointments_clean.join(
        doctors_df.select("doctor_id", "specialization"),
        "doctor_id",
        "inner"
    )
    .groupBy("specialization", "year_int")
    .agg(count("appointment_id").alias("yearly_appointment_count"))
    .orderBy("year_int", "yearly_appointment_count", ascending=False)
)

print("Yearly appointment count per specialization:")
yearly_specialization_appointments.show()
```

▶ (3) Spark Jobs

▶ appointments_clean: pyspark.sql.dataframe.DataFrame = [appointment_id: integer, appointment_timestamp: timestamp ... 8 more fields]

▶ yearly_specialization_appointments: pyspark.sql.dataframe.DataFrame = [specialization: string, year_int: integer ... 1 more field]

ophthalmology	2023	6
nephrology	2023	5
allergists	2023	5

Transformation 5: Yearly revenue trend for each specialization

```
# Transformation 8: Yearly revenue trend for each specialization
specialization_revenue_trend = revenue_by_doctor_year.groupBy("specialization", "appointment_year").agg(
    sum("yearly_revenue").alias("total_yearly_revenue_specialization"),
    count("doctor_id").alias("number_of_doctors")
).withColumn(
    "avg_revenue_per_doctor", col("total_yearly_revenue_specialization") / col("number_of_doctors")
)

print("Specialization revenue trend:")
specialization_revenue_trend.orderBy("appointment_year", "total_yearly_revenue_specialization", ascending=False).show()
```

▶ (5) Spark Jobs

▶ specialization_revenue_trend: pyspark.sql.dataframe.DataFrame = [specialization: string, appointment_year: string ... 3 more fields]

obstetric anes...	2023	5815321.0	4	1453830.25
geriatrician	2023	4844910.0	2	2422455.0
pediatrics	2023	4644340.0	3	1548113.3333333333
family medicine	2023	4568693.0	2	2284346.5
dermatology	2023	4316799.0	3	1438933.0
ophthalmology	2023	4219545.0	4	1054886.25
allergists	2023	4035233.0	5	807046.6

Find the most common procedure

▶ ✓ 2 days ago (<1s)

```
procedures_df = spark.read.format("parquet").load(f"abfss://source@projectadf.dfs.core.windows.net/medic
```

▶ (1) Spark Jobs

▶ 📄 procedures_df: pyspark.sql.dataframe.DataFrame = [procedure_id: integer, procedure_name: string ... 2 more fields]

▶ ✓ 2 days ago (<1s)

```
from pyspark.sql.functions import count
```

```
common_procedure = (  
    procedures_df  
    .groupBy("procedure_name")  
    .agg(count("*").alias("procedure_count"))  
    .orderBy("procedure_count", ascending=False)  
)
```

```
common_procedure.show()
```

▶ (2) Spark Jobs

▶ 📄 common_procedure: pyspark.sql.dataframe.DataFrame = [procedure_name: string, procedure_count: long]

Comprehensive Ger...	24
Interventional Ra...	23
Laser Therapy For...	22
Sedation For Mino...	22
General Surgery	22
Dermatologic Surg...	22

Rank by specialization

2 days ago (1s)

24

```
from pyspark.sql.window import Window
from pyspark.sql.functions import rank, col, sum

# Base: doctors with career revenue (before joining everything else)
doctor_revenue_base = total_revenue_by_doctor_year.groupBy("doctor_id").agg(
    sum("total_yearly_revenue").alias("total_revenue")
).join(
    doctors_df.select("doctor_id", "doctor_name", "specialization"),
    "doctor_id",
    "inner"
)

# Define ranking window by specialization
specialization_rank_window = Window.partitionBy("specialization").orderBy(col("total_revenue").desc())

# Add rank column
doctor_performance_df = doctor_revenue_base.withColumn(
    "specialization_rank",
    rank().over(specialization_rank_window)
)

# Preview top 20
doctor_performance_df.limit(20).display()
```

(7) Spark Jobs

doctor_performance_df: pyspark.sql.dataframe.DataFrame = [doctor_id: integer, total_revenue: double ... 3 more fields]

doctor_revenue_base: pyspark.sql.dataframe.DataFrame = [doctor_id: integer, total_revenue: double ... 2 more fields]

Table +

	¹ ₃ doctor_id	¹ ₂ total_revenue	^A _C doctor_name	^A _C specialization	¹ ₃ specialization_rank
1	975	2173939	Hettie	allergists	1
2	619	1987601	Shannah	allergists	2
3	430	1691230	Eolanda	allergists	3
4	742	908837	Gui	allergists	4

```
25
from pyspark.sql.functions import coalesce, lit, sum, current_timestamp

# Start with doctor-level base info
final_summary_df = doctors_df.select(
    "doctor_id",
    "doctor_name",
    "specialization",
    "contact_info"
)

# Skip doctor_total_appointments join since you don't need it

# Join with revenue by year (career total revenue)
final_summary_df = final_summary_df.join(
    total_revenue_by_doctor_year.groupBy("doctor_id")
    .agg(sum("total_yearly_revenue").alias("total_revenue")),
    "doctor_id",
    "left"
).withColumn("total_revenue", coalesce(col("total_revenue"), lit(0.0)))

# Join with specialization demand classification
final_summary_df = final_summary_df.join(
    specialization_demand_yearly.select(
        "specialization",
        "specialization_demand_level"
    ),
    "specialization",
    "left"
).withColumn("specialization_demand_level", coalesce(col("specialization_demand_level"), lit("Unknown")))

# Join with specialization workload classification
final_summary_df = final_summary_df.join(
    specialization_workload_classified.select(
        "specialization",
        col("total_appointments").alias("specialization_total_appointments"),
        "workload_level"
    ),
    "specialization",
    "left"
).withColumn("specialization_total_appointments", coalesce(col("specialization_total_appointments"), lit(0))) \
.withColumn("workload_level", coalesce(col("workload_level"), lit("Unknown")))

# Add lineage timestamp
final_summary_df = final_summary_df.withColumn("ingestion_date", current_timestamp())
```

```
26
%sql
drop table if exists healthcare_analysis.specialization_summary
OK

27
final_summary_df.write.mode("overwrite").format("delta").saveAsTable("healthcare_analysis.specialization_summary")

▶ (18) Spark Jobs

28
final_summary_df.write.mode("overwrite").parquet("f"abfss://destination@projectadf.dfs.core.windows.net/specialization_summary")

▶ (13) Spark Jobs
```


To visualize the transformed data, create two more notebooks inside the data analysis folder

Data_analysis/Patient_analysis

Day of Week & Weekend Analysis

2 days ago (2s)

```
%sql
-- Count appointments per day of week
SELECT
    day_name,
    day_type,
    COUNT(*) AS total_appointments
FROM healthcare_analysis.patient_appointment_summary
GROUP BY day_name, day_type
ORDER BY total_appointments DESC;
```

(2) Spark Jobs

_sqldf: pyspark.sql.dataframe.DataFrame = [day_name: string, day_type: string ... 1 more field]

	day_name	day_type	total_appointments
1	Monday	Weekday	63
2	Wednesday	Weekday	62
3	Friday	Weekday	59
4	Thursday	Weekday	54
5	Sunday	Weekend	53
6	Saturday	Weekend	52
7	Tuesday	Weekday	51

7 rows | 2.30s runtime

This result is stored as _sqldf and can be used in other Python cells.

Peak duration of Month (Early / Mid / Late Month)

2 days ago (1s)

```
%sql
SELECT
    day_bucket,
    COUNT(*) AS total_appointments
FROM healthcare_analysis.patient_appointment_summary
GROUP BY day_bucket
ORDER BY total_appointments DESC;
```

(2) Spark Jobs

_sqldf: pyspark.sql.dataframe.DataFrame = [day_bucket: string, total_appointments: long]

	day_bucket	total_appointments
1	Late Month	161
2	Early Month	120
3	Mid Month	113

First vs Returning Patients

2 days ago (1s)

```
%sql
SELECT
  is_first_appointment,
  COUNT(*) AS total_appointments,
  COUNT(DISTINCT patient_id) AS unique_patients
FROM healthcare_analysis.patient_appointment_summary
GROUP BY is_first_appointment;
```

(3) Spark Jobs

_sqldf: pyspark.sql.dataframe.DataFrame = [is_first_appointment: boolean, total_appointments: long, ...]

	is_first_appointment	total_appointments	unique_patients
1	true	219	219
2	false	175	93

Top 10 patients based on their payment details

2 days ago (1s)

8

```
%sql
SELECT
  patient_id,
  patient_name,
  SUM(total_amount) AS total_payment
FROM healthcare_analysis.patient_appointment_summary
GROUP BY patient_id, patient_name
ORDER BY total_payment DESC
LIMIT 10;
```

(2) Spark Jobs

_sqldf: pyspark.sql.dataframe.DataFrame = [patient_id: integer, patient_name: string ... 1 more field]

	patient_id	patient_name	total_payment
1	368	Stephanie Agle	27493624
2	779	Candi Shaver	13134572
3	381	Chickie Hazlett	7298356
4	961	Ruthe Garbe	5668260
5	694	Paola Swigart	5529024
6	409	Netty Moseley	5370324
7	339	Mellicent Viddah	4373994
8	546	Aimil Suzetta	4347878
9	994	Gui Turne	4312515
10	817	Trixi Skurnik	4038372

Data_analysis/Patient_analysis

Number of doctors in each specialization

2 days ago (2s)

%sql

SELECT specialization, COUNT(DISTINCT doctor_id) AS number_of_doctors
FROM healthcare_analysis.specialization_summary
GROUP BY specialization
ORDER BY number_of_doctors DESC;

(3) Spark Jobs

_sqlIdf: pyspark.sql.dataframe.DataFrame = [specialization: string, number_of_doctors: long]

Table Visualization 1

	specialization	number_of_doctors
1	infectious disease	37
2	oncologist	35
3	gastroenterology	33
4	otolaryngologists	32
5	emergency medicine	31
6	dermatology	29
7	allergists	28
8	internists	28
9	pulmonologists	27
10	nephrology	26
11	ophthalmology	25
12	anesthesiology	25
13	neurology	24
14	obstetric anesthesiologis...	24
15	surgery	24

24 rows | 2.30s runtime

Doctors with highest revenue in each specialization

2 days ago (1s)

%sql

SELECT specialization, doctor_id, doctor_name, total_revenue
FROM (
 SELECT
 specialization,
 doctor_id,
 doctor_name,
 total_revenue,
 ROW_NUMBER() OVER (PARTITION BY specialization ORDER BY total_revenue DESC) AS rank
 FROM healthcare_analysis.specialization_summary
) ranked
WHERE rank = 1;

(2) Spark Jobs

_sqlIdf: pyspark.sql.dataframe.DataFrame = [specialization: string, doctor_id: integer ..., 2 more fields]

Table

	specialization	doctor_id	doctor_name	total_revenue
1	allergists	975	Hettie	2173939
2	anesthesiology	792	Leanna	3680845
3	cardiology	237	Suzette	1830079
4	critical care medicine	452	Minne	3593294
5	dermatology	801	Brooks	3436703
6	emergency medicine	877	Vevay	2113058
7	endocrinologist	300	Roxane	1889420
8	family medicine	189	Max	3283643
9	gastroenterology	129	Aurelie	3204079
10	geriatrician	667	Gloria	5846564
11	hospice and palliative care	407	Bill	3436703
12	infectious disease	574	Ronna	2206483
13	internists	362	Charissa	1896039
14	nephrology	443	Renie	1354711
15	neurology	976	Netty	3283643

24 rows | 0.79s runtime

2 days ago (1s)

```
%sql
-- Highest demand specialization
SELECT specialization, specialization_demand_level
FROM healthcare_analysis.specialization_summary
WHERE specialization_demand_level = 'High Demand'
GROUP BY specialization, specialization_demand_level
ORDER BY COUNT(doctor_id) DESC
LIMIT 1;
```

(2) Spark Jobs

_sqldf: pyspark.sql.dataframe.DataFrame = [specialization: string, specialization_d

Table +

	specialization	specialization_demand_level
1	infectious disease	High Demand

2 days ago (1s)

```
%sql
-- Lowest demand specialization
SELECT specialization, specialization_demand_level
FROM healthcare_analysis.specialization_summary
WHERE specialization_demand_level = 'Low Demand'
GROUP BY specialization, specialization_demand_level
ORDER BY COUNT(doctor_id) ASC
LIMIT 1;
```

(2) Spark Jobs

_sqldf: pyspark.sql.dataframe.DataFrame = [specialization: string, specialization_den

Table +

	specialization	specialization_demand_level
1	hospice and palliative care	Low Demand

Doctor who earns the highest in the hospital

+ Code

2 days ago (<1s)

```
%sql
SELECT doctor_id, doctor_name, specialization, total_revenue
FROM healthcare_analysis.specialization_summary
ORDER BY total_revenue DESC
LIMIT 1;
```

(1) Spark Jobs

_sqldf: pyspark.sql.dataframe.DataFrame = [doctor_id: integer, doctor_name: string ... 2 more fields]

Table +

	doctor_id	doctor_name	specialization	total_revenue
1	667	Gloria	geriatrician	5846564

Here is the link of [notebook files](#) we have used in this project

Step-3 : Create a Data Factory

Create a new Azure Data Factory to implement a serverless data processing pipeline.

The screenshot displays the Microsoft Azure portal interface. The top navigation bar includes the Microsoft Azure logo, a search bar, and user information. The main content area shows the 'Create Data Factory' wizard, which is currently on the 'Review + create' step. The wizard includes sections for 'Project details' (Subscription, Resource group) and 'Instance details' (Name, Region, Version). Below the wizard, there are buttons for 'Previous', 'Next', and 'Review + create'. A 'Give feedback' link is also present.

The second part of the screenshot shows the 'Overview' page of the newly created Data Factory, 'Microsoft.DataFactory-20250825154801'. The page displays the deployment status as 'Your deployment is complete' and provides details such as the deployment name, subscription, resource group, start time, and correlation ID. A 'Go to resource' button is available. A 'Give feedback' link is also present.

A 'Deployment succeeded' notification is visible in the top right corner, stating: 'Deployment 'Microsoft.DataFactory-20250825154801' to resource group 'rg-azuser4031_mml.local-yVleu' was successful.' Below the notification, there are links to 'Pin to dashbo...' and 'Go to resource gr...'. The right sidebar contains several recommendations: 'Cost management', 'Microsoft Defender for Cloud', 'Free Microsoft tutorials', and 'Work with an expert'.

Next, launch the Azure Data Factory Studio that is created.

Microsoft Azure

Search resources, services, and docs (G+)

Copilot

azuser4031_mml.local@...
TECHADEMY LEARNING SOLUTIONS

Home > Microsoft.DataFactory-20250825154801 | Overview > rg-azuser4031_mml.local-yVJeu >

project-adf06
Data factory (V2)

Summary of the properties of this Data factory (V2). List triggers associated with this Data factory (V2). How do I troubleshoot pipeline failures in this Data factory (V2)?

Search

Overview

Activity log

Access control (IAM)

Tags

Diagnose and solve problems

Resource visualizer

Settings

Getting started

Monitoring

Automation

Help

Essentials

Resource group (move) : rg-azuser4031_mml.local-yVJeu

Status : Succeeded

Location : Central India

Subscription (move) : MML Learners

Subscription ID : 2a3c6418-97b9-4d96-a24b-2c2d7633d375

Type : Data factory (V2)

Getting started : [Quick start](#)

JSON View

Azure Data Factory Studio

Launch studio

Quick Starts

Tutorials


Template Gallery

Training Modules

<https://adf.azure.com/en/home?factoryName=%2Fsubscriptions%2F2a3c6418-97b9-4d96-a24b-2c2d7633d375>

Define a linked service for the Azure Storage account, Below is the process of creating a linked service.

New linked service

 Azure Databricks [Learn more](#)

Name *

adf_linked_service

Description

Connect via integration runtime *

☒ AutoResolveIntegrationRuntime

Account selection method *

☒ From Azure subscription ☐ Enter manually

Azure subscription *

MML Learners (2a3c6418-97b9-4d96-a24b-2c2d7633d375)

Databricks workspace *

adfworkspace01

Select cluster

☐ New job cluster ☒ Existing interactive cluster ☐ Existing instance pool

Databrick Workspace URL *

https://adb-3235587147928749.9.azuredatabricks.net

Authentication type *

Create Cancel

Test connection

New linked service

 Azure Databricks [Learn more](#)

Databricks workspace *

adfworkspace01

Select cluster

☐ New job cluster ☒ Existing interactive cluster ☐ Existing instance pool

Databricks Workspace URL *

https://adb-3235587147928749.9.azure.databricks.net

Authentication type *

Access Token

☒ Access token ☐ Azure Key Vault

Access token *

.....

Choose from existing clusters *

adf-project-cluster

Annotations


+ New

> Parameters

> Advanced

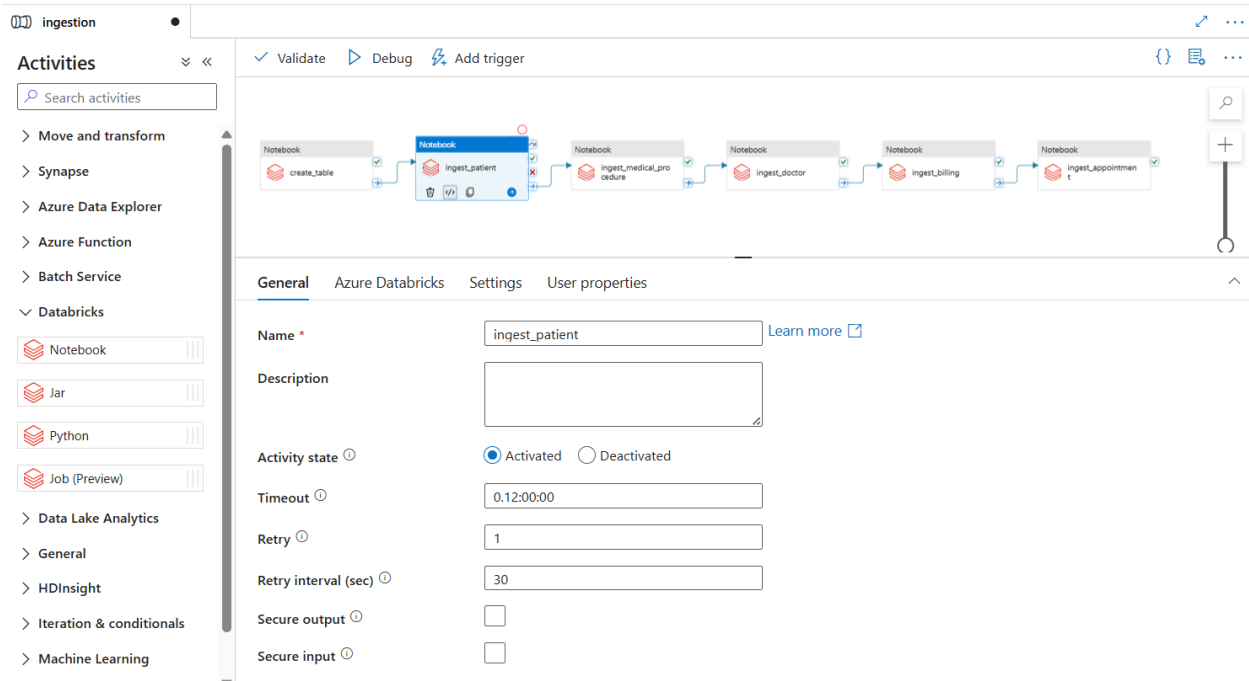
Create

Cancel

 Test connection

Creating Ingestion pipeline

In the Activity tab, select databricks notebook activity and now add 6 notebook activity to create the pipeline and configure the activity for each notebook like below. Once configure click publish all then click on add trigger to run the pipeline



The screenshot displays the Azure Data Factory (ADF) interface. On the left, the 'Activities' pane shows the 'Databricks' category expanded, with 'Notebook' selected. The main canvas shows a pipeline named 'ingestion' with six notebook activities connected in sequence: 'create_table', 'ingest_patient', 'ingest_medical_procedure', 'ingest_doctor', 'ingest_billing', and 'ingest_appointments'. The 'ingest_patient' activity is selected, and its configuration is shown in the bottom pane. The configuration includes the following fields:

- Name:** ingest_patient
- Description:** (empty text box)
- Activity state:** ☒ Activated ☐ Deactivated
- Timeout:** 0.12:00:00
- Retry:** 1
- Retry interval (sec):** 30
- Secure output:** ☐
- Secure input:** ☐

Microsoft Azure | Data Factory | project-adf06

Would you like to see Data Factory inside of Microsoft Fabric, Microsoft's newest cloud-first data analytics SaaS platform? Click [here](#) to get started with Fabric.

Factory Resources

- Pipelines (3)
 - analysis
 - ingestion
 - transformation
- Change Data Capture (preview) 0
- Datasets 0
- Data flows 0
- Power Query 0

Ingestion | **transformation** | **analysis**

Validate | Debug | Add trigger

Notebook

- create_table
- ingest_patient
- in ce

General | Azure Databricks | **Settings** | User properties

Notebook path *

> Base parameters

> Append libraries

+ New

Notifications

- Dismiss all
- Publishing completed**
Successfully published
a minute ago
- Publishing completed**
Successfully published
3 minutes ago
- Publishing completed**
Successfully published
6 minutes ago
- Successfully created**
Successfully created adf_linked_service (Linked service).
17 minutes ago

Close

Similarly for the Transformation pipeline and Analysis pipeline we do the same.

ingestion | **transformation** | **analysis**

Validate | Debug | Add trigger

Notebook

- patient_summary
- specialization_summary

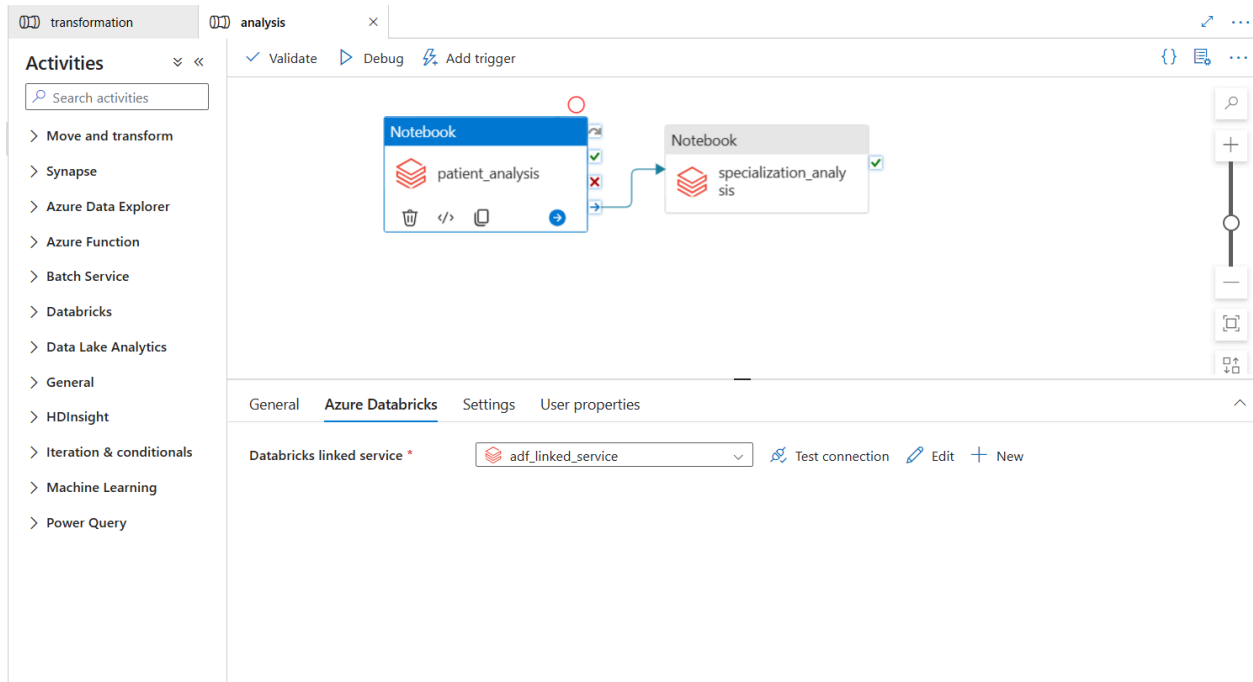
General | Azure Databricks | **Settings** | User properties

Notebook path *

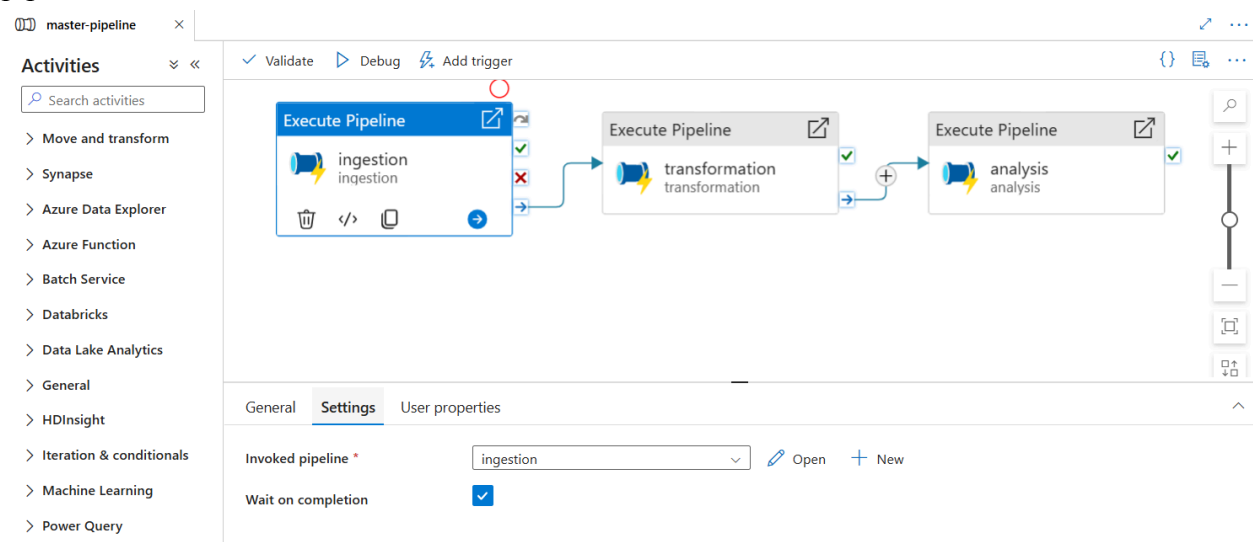
Browse Open

> Base parameters

> Append libraries



Create Master Pipeline by selecting execute pipeline in the general activity section and map the ingestion, transformation and analysis pipeline one after the other to create the complete master pipeline.



Microsoft Azure | Data Factory | project-adf06

Search

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» <<

Dashboards

Runs

Pipeline runs

Trigger runs

Change Data Capture (previ...

Runtimes & sessions

Integration runtimes

Data flow debug

Notifications

Alerts & metrics

All pipeline runs > master-pipeline - Activity runs

Rerun Cancel Refresh Update pipeline List Gantt

Execute Pipeline ingestion ingestion

Execute Pipeline transformation transformation

Execute Pipeline analysis analysis

Activity runs

Pipeline run ID c246209e-a528-48ca-b11a-823b74af6e73

All status

Monitor in Azure Metrics Export to CSV

Showing 1 - 1 items

Activity name	Activity st...	Activit...	Run start	Duration	Integration runtime	User prop...	Activity run ID
ingestion	In progress	Execute Pipelin...	8/25/2025, 4:19:12 PM	Less than 1s			1d53f7f8-fcae-4f96-i

Output

Successful Output Generated:

- Validate and Debug the pipeline created to see the results of the execution.
- It shows the Activity Status as **Succeeded** which means our pipeline successfully ingested, transformed and analyzed the data.

Activity runs

Pipeline run ID c246209e-a528-48ca-b11a-823b74af6e73

Succeeded

Monitor in Azure Metrics Export to CSV

Showing 1 - 3 items





Activity name	Activity st...	Activit...	Run start	Duration	Integration runtime	User prop...	Activity run ID
analysis	Succeeded	Execute Pipelin...	8/25/2025, 4:25:15 PM	1m 13s			6e270475-dc42-428f
transformation	Succeeded	Execute Pipelin...	8/25/2025, 4:23:30 PM	1m 45s			975f70f4-c437-481c
ingestion	Succeeded	Execute Pipelin...	8/25/2025, 4:19:12 PM	4m 18s			1d53f7f8-fcae-4f96-i

In the source container we can see the processed data is stored

source

Authentication method: Access key ([Switch to Microsoft Entra user account](#))

Showing all 5 items










<input type="checkbox"/>	Name	Last modified	Access tier
<input type="checkbox"/>	 appointments	8/25/2025, 2:58:11 PM	
<input type="checkbox"/>	 billing	8/25/2025, 2:57:24 PM	
<input type="checkbox"/>	 doctors	8/25/2025, 2:55:28 PM	
<input type="checkbox"/>	 medical_procedures	8/25/2025, 2:54:35 PM	
<input type="checkbox"/>	 patients	8/25/2025, 2:53:33 PM	

source >  appointments

Authentication method: Access key ([Switch to Microsoft Entra user account](#))

Only show active objects ☐

Showing all 8 items

<input type="checkbox"/>	Name	Last modified	Access tier	Blob type	Size	Lease state
<input type="checkbox"/>	 [-]					...
<input type="checkbox"/>	 _SUCCESS	8/25/2025, 4:23:15 PM	Hot (Inferred)	Block blob	0	Available ...
<input type="checkbox"/>	 _committed_5570965616819959164	8/25/2025, 4:23:10 PM	Hot (Inferred)	Block blob	233 B	Available ...
<input type="checkbox"/>	 _committed_6198646254894929306	8/25/2025, 2:58:11 PM	Hot (Inferred)	Block blob	123 B	Available ...
<input type="checkbox"/>	 _committed_9115898469978707106	8/25/2025, 4:23:15 PM	Hot (Inferred)	Block blob	223 B	Available ...
<input type="checkbox"/>	 _committed_vacuum5847446971087808802	8/25/2025, 4:23:10 PM	Hot (Inferred)	Block blob	96 B	Available ...
<input type="checkbox"/>	 _started_5570965616819959164	8/25/2025, 4:23:10 PM	Hot (Inferred)	Block blob	0	Available ...
<input type="checkbox"/>	 _started_9115898469978707106	8/25/2025, 4:23:15 PM	Hot (Inferred)	Block blob	0	Available ...
<input type="checkbox"/>	 part-00000-tid-9115898469978707106-fb2945ab-b10a-49e5-...	8/25/2025, 4:23:15 PM	Hot (Inferred)	Block blob	12.94 KiB	Available ...

Similarly in the destination container we can see our transformed data is stored for the further analysis



[+ Add Directory](#) [↑ Upload](#) [↻ Refresh](#) | [🗑 Delete](#) [📄 Copy](#) [📄 Paste](#) [🔄 Rename](#) [🔑 Acquire lease](#) [🔑 Break lease](#) [⚙ Edit columns](#)

destination

Authentication method: Access key ([Switch to Microsoft Entra user account](#))

Only show active objects ☐

Showing all 2 items

<input type="checkbox"/>	Name	Last modified	Access tier	Blob type	Size	Lease state
<input type="checkbox"/>	 patient_appointment_summary	8/25/2025, 3:00:45 PM				
<input type="checkbox"/>	 specialization_summary	8/25/2025, 3:06:27 PM				

Strategies for Implementing a Serverless Data Processing Pipeline with Azure Data Factory and Azure Databricks

1. Use Serverless and On-Demand Compute

Leverage serverless Databricks SQL warehouses or auto-terminating clusters to avoid idle costs. Trigger pipeline execution only when needed using ADF triggers.

2. Decouple Storage and Compute

Store raw, intermediate, and processed data in Azure Data Lake Gen2 or Blob Storage. Use Delta Lake for schema enforcement, transactional consistency, and performance.

3. Modular Pipeline Design

Design pipelines as independent stages for ingestion, validation, transformation, and loading. Use parameters and variables in ADF to make them environment-agnostic.

4. Databricks for Heavy Transformations

Utilize Spark for large-scale ETL, streaming, machine learning, and graph processing. Use Delta Live Tables (DLT) for reliable declarative ETL.

5. Data Layout Optimization

Apply partitioning, Z-ordering, compression, and caching in Delta Lake to enhance query speed and storage efficiency.

6. Security and Governance

Use Managed Identity for secure access to storage. Enable Unity Catalog for centralized data governance, access control, and lineage tracking.

7. Monitoring and Logging

Monitor pipelines through Azure Monitor and Log Analytics. Track Spark UI logs, job performance, and cluster utilization, with alerts for errors or performance drops.

8. Cost Management

Enable auto-termination for clusters, right-size based on workload, and use spot instances where possible. Track costs with Azure Cost Management and budgets.

9. CI/CD and DevOps Integration

Integrate ADF pipelines and Databricks notebooks with GitHub or Azure DevOps. Use Databricks Repos for version control and CI/CD pipelines for deployment automation.

10. Error Handling and Retry Mechanisms

Implement retry policies in ADF, configure dead-letter queues for bad records, and log errors for monitoring and alerting.

Conclusion

This project successfully implemented a serverless data processing pipeline using Azure Data Factory (ADF) and Azure Databricks, enabling seamless data ingestion, transformation, and analysis. The integration of these Azure services provided a scalable, cost-efficient, and modular solution for handling large-scale data workflows.

Successful Orchestration of Pipelines

Azure Data Factory served as the central orchestrator, coordinating three separate pipelines for ingestion, transformation, and analysis. By combining these pipelines into a master pipeline, the project ensured a clear workflow structure and efficient execution with dependency management.

Efficient Data Processing with Databricks

Azure Databricks provided the computational power for complex transformations and analytical tasks. Its distributed Spark engine enabled large-scale data processing, while Delta Lake ensured transactional consistency, schema enforcement, and optimized query performance.

Monitoring and Control

Although the pipeline was executed through manual triggers, monitoring and logging were effectively handled via ADF run history and Databricks job metrics. This allowed for effective tracking, debugging, and performance evaluation.