

## When to Reset Auto Loader in Databricks

### When to Reset Auto Loader

You might want to reset Auto Loader if:

1. A file was missed due to a crash or misconfiguration.
2. You updated logic (e.g., transformations or schema).
3. Files were partially written or failed mid-batch.
4. You want to **reprocess everything** from scratch.

### What Resetting Actually Means

Resetting Auto Loader means:

- **Deleting the checkpoint folder** — so Spark **forgets what it already processed**.
- (Optional) **Deleting the output Delta table or path** — if you want to **fully reload the data**.

### Important Warning

❗ Resetting the checkpoint will cause **all files in the input directory** to be **reprocessed**, even those already written to the target table — unless deduplication logic is used.

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### Step-by-Step: Reset Auto Loader

Folder Structure:

```

📁 /mnt/data/autoloader/incoming/
    ♦ Source files (CSV, JSON, etc.)

📁 /mnt/data/autoloader/schema/people/
    ♦ Schema info used by Auto Loader

📁 /mnt/data/autoloader/checkpoints/people/
    ├── commits/      ✅ Batch success logs
    ├── offsets/     📄 File read progress
    ├── metadata/    ⚙️ Job config and Spark info
    ├── sources/     👁️ Files seen per batch
    └── state/       🧠 Aggregation state (only if needed)

📁 /mnt/data/bronze/people/
    ♦ Delta table output (cleaned/transformed data)
```

## The Databricks: **Auto-Loader**    **Data Processed** vs. **Yet to Be Processed**

Config Path	Internally Controls or Maps To
source_path	sources/, offsets/ (files discovered + read)
schema_path	Maintains schema inference snapshots
checkpoint_path	Creates commits/, offsets/, sources/, etc.
target_path	Stores the final Delta data output

**Assume your setup:**

```
python
CopyEdit
source_path = "/mnt/data/autoloader/incoming/"
schema_path = "/mnt/data/autoloader/schema/people/"
checkpoint_path = "/mnt/data/autoloader/checkpoints/people/"
target_path = "/mnt/data/bronze/people/"
```

Once Auto Loader starts writing, this folder will contain:  
Target\_path is the **location on DBFS or cloud storage** where **processed data is written** .

```
/mnt/data/bronze/people/
├─ _delta_log/           # 📄 Transaction Logs for Delta table (JSON + checkpoint files)
├─ part-00000-...snappy.parquet # 📦 Actual data files in Parquet format
├─ part-00001-...snappy.parquet
└─ ...
```

Folder / File	Description
_delta_log/	Stores metadata about the table (transaction history, schema changes, commit logs)
*.parquet	Your actual <b>Ingested and transformed data</b>
(No checkpoint/ here) Checkpoint is stored separately under checkpoint_path, not here	

**Register it as Delta Table** , below is the run query:

```
CREATE TABLE bronze_people
USING DELTA
LOCATION '/mnt/data/bronze/people/'

SELECT * FROM bronze_people;
```

### Summary

Term	Path	Stores What?
target_path	/mnt/data/bronze/people/	Delta table (data + metadata)
Contents	_delta_log/ + *.parquet	All processed data from Auto Loader pipeline

**Note:**

If the table is not registered, you can still read it using the **Delta table path**, but you **can't query it by name** in SQL or Unity Catalog.

**You can't see data lineage in Unity Catalog** if the table is **not registered** – lineage tracking only works for **registered tables** in a **Unity Catalog-enabled metastore**.

## 1. Stop the Streaming Job

You can do this from the notebook UI, Jobs tab, or by calling `.stop()` if you've assigned it to a variable:

```
python
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query = df_transformed.writeStream...start()
query.stop()
```

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## 2. Delete the Checkpoint Directory

```
python
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dbutils.fs.rm(checkpoint_path, recurse=True)
```

This erases:

- commits/
- offsets/
- sources/
- state/

→ Spark no longer knows which files were already processed.

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## (Optional) 3. Delete the Output Delta Table

If you want to **rebuild from scratch**:

```
python
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dbutils.fs.rm(target_path, recurse=True)
```

Or if registered as a table:

```
sql
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DROP TABLE IF EXISTS bronze.people;
```

---

## 4. Re-run Your Auto Loader Job

Use the same logic from the document:

```
python
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from pyspark.sql.functions import current_timestamp, input_file_name, upper, col

df = (
    spark.readStream
        .format("cloudFiles")
        .option("cloudFiles.format", "csv")
        .option("cloudFiles.inferColumnTypes", "true")
        .option("cloudFiles.schemaLocation", schema_path)
        .load(source_path)
```

```
)

df_transformed = (
    df.withColumn("FristName", upper(col("FirstName")))
      .withColumn("ingestion_timestamp", current_timestamp())
      .withColumn("source_file", input_file_name())
)

df_transformed.writeStream \
    .format("delta") \
    .option("checkpointLocation", checkpoint_path) \
    .outputMode("append") \
    .start(target_path)
```

### Optional: Add Deduplication to Avoid Double Processing

If you can't delete the output but still want to reprocess without duplicating:

```
python
CopyEdit
from pyspark.sql.functions import expr

df_deduped = df_transformed.dropDuplicates(["id", "source_file"])

# Or add a hash-based deduplication
```

### Summary: Reset Guide

Step	Action
Stop the stream	.stop() or notebook control
Delete checkpoint	dbutils.fs.rm(checkpoint_path, recurse=True)
Delete output (optional)	dbutils.fs.rm(target_path, recurse=True)
Restart the job	Run your Auto Loader pipeline again

### Pros of Unregistered (Path-Based) Tables

### Cons of Not Registering

Advantage	Description
<b>Simple setup</b>	No need to create a table in metastore
<b>Flexible for ad-hoc use</b>	Useful for temporary or dev pipelines
<b>Easier testing</b>	You can write and delete freely without affecting production tables
<b>Still fully readable</b>	Use .read.format("delta").load("/path/") in PySpark
<b>Portable</b>	Can be copied or moved without breaking SQL references

Limitation	Description
<b>No SQL name</b>	Can't use SELECT * FROM table_name — must use path
<b>No Unity Catalog support</b>	No lineage, governance, or RBAC features
<b>Harder collaboration</b>	Other users must know the exact path to access
<b>No lineage tracking</b>	Data lineage graph in Unity Catalog won't include it
<b>No data discovery</b>	Won't show up in catalogs, schemas, or SHOW TABLES
<b>Prone to accidental overwrite</b>	No metastore protection for concurrent writes

## Trainee Q&A: How Auto Loader Handles Files Across Batches

- Mentor (IT Architect)
- Trainee (Junior Data Engineer)

**Auto Loader** is a high-performance, scalable file ingestion tool provided by Databricks for ingesting new data files from cloud storage (like AWS S3, Azure Data Lake, or Google Cloud Storage) **automatically and incrementally** using **Databricks Structured Streaming**.

### Purpose:

- Watches a directory for **new files only** — no need to reprocess old data.
- Supports **schema inference** and **evolution**.
- Handles **millions of files** efficiently using file notification services.
- Works with formats like **CSV, JSON, Parquet, Avro**, and more.
- Ideal for implementing **Bronze layer ingestion** in Delta Lake.

### Trainee

Hey, I've been exploring Auto Loader in Databricks, and I've got a question. Let's say we have 5 files to ingest — how exactly are they represented in the checkpoint directory?

Specifically in commits/ and sources/ — does sources track all 5 files or only the ones from the current micro-batch?

### Mentor

That's a great question! Auto Loader organizes metadata in a very structured way — and understanding it will help you debug and optimize streaming jobs efficiently.

Let me break it down for you. There are **two possible ways** those 5 files could be processed, depending on when they arrive and your stream's trigger setting.

### Mentor

#### Option A: All 5 files arrive together (one micro-batch)

If all 5 files are discovered **before the next trigger fires**, Auto Loader groups them into a **single batch**.

You'll see:

- commits/0 → indicating **batch 0 was committed**
- sources/0 → listing all files seen in this batch:

```
json
CopyEdit
"seenFiles": [
  "people_1.csv",
  "people_2.csv",
  "people_3.csv",
  "people_4.csv",
  "people_5.csv"
]
```

So in this case, sources/0 alone shows all 5 files — and they were all committed in batch 0.

**Trainee:**

Got it — so if all files arrive close together, one batch can handle all of them. What if the files arrive at different times?

**Mentor**

**Option B: Files arrive at different times (multiple batches)**

Let's say:

- 3 files arrive first,
- and 2 more come in **10 seconds later**.

With a typical trigger interval (like every 10 seconds), Spark will process them in **two separate batches**:

- commits/0 → batch 0
  - sources/0 → "seenFiles": ["people\_1.csv", "people\_2.csv", "people\_3.csv"]
- commits/1 → batch 1
  - sources/1 → "seenFiles": ["people\_4.csv", "people\_5.csv"]

So the files are **split across multiple sources/N files**, but all 5 are still tracked.

**Trainee:**

Oh, I see. So even though they're split across batches, the total seen files still add up to 5. Makes sense!

**Final Takeaway**

Folder	What It Reflects
commits/	Number of <b>micro-batches</b> (e.g., 0, 1, 2...)
sources/	Tracks the <b>files seen in each batch</b>
Total seenFiles	Equals all files that were <b>actually processed</b>

So, even if you process 5 files over 1, 2, or 10 batches, the total number of seenFiles across sources/ will still be 5.

**Trainee:**

That clears it up perfectly! So it's the **batches** that control the file grouping, not the number of files per se.

**Mentor:**

Exactly! It's **time-based batching**, not file-count-based. And once you understand how commits/ and sources/ align, it's much easier to track and debug your Auto Loader pipelines.

## Appendix:

### Sample Auto Loader Code

```
python
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from pyspark.sql.functions import current_timestamp, input_file_name, upper, col

# Read data using Auto Loader
df = (
    spark.readStream
        .format("cloudFiles")
        .option("cloudFiles.format", "csv") # File format
        .option("cloudFiles.inferColumnTypes", "true") # Infer schema
        .option("cloudFiles.schemaLocation", "/mnt/data/autoloader/schema/employee/") # Where schema is stored
        .load("/mnt/data/autoloader/incoming/") # Input folder
)

# Apply transformations
df_transformed = (
    df.withColumn("department", upper(col("department")))
        .withColumn("ingestion_timestamp", current_timestamp())
        .withColumn("source_file", input_file_name())
)

# Write to Delta Lake with checkpointing
(
    df_transformed.writeStream
        .format("delta")
        .option("checkpointLocation", "/mnt/data/autoloader/checkpoints/employee/") # Required
        .outputMode("append")
        .start("/mnt/data/bronze/employee") # Bronze table path
)
```

### AutoLoader

Config : Without Trigger	Config : With Trigger																		
<pre>df.writeStream \     .format("delta") \     .option("checkpointLocation", "/mnt/checkpoints/people") \     .start("/mnt/data/delta/bronze_people")</pre>	<pre>df.writeStream \     .format("delta") \     .option("checkpointLocation", "/mnt/checkpoints/people") \     .trigger(processingTime="5 seconds") \     .start("/mnt/data/delta/bronze_people")</pre>																		
<b>Behavior:</b> <table border="1"> <thead> <tr> <th>Time</th><th>Action</th></tr> </thead> <tbody> <tr> <td>00:00</td><td>Spark sees people_1.csv and processes it in <b>batch 0</b> immediately</td></tr> <tr> <td>00:03</td><td>Spark detects people_2.csv and runs <b>batch 1</b></td></tr> <tr> <td>00:06</td><td>Spark sees people_3.csv and starts <b>batch 2</b></td></tr> <tr> <td>...</td><td>Spark polls continuously with <b>no delay</b></td></tr> </tbody> </table>	Time	Action	00:00	Spark sees people_1.csv and processes it in <b>batch 0</b> immediately	00:03	Spark detects people_2.csv and runs <b>batch 1</b>	00:06	Spark sees people_3.csv and starts <b>batch 2</b>	...	Spark polls continuously with <b>no delay</b>	<b>Behavior:</b> <table border="1"> <thead> <tr> <th>Time</th><th>Action</th></tr> </thead> <tbody> <tr> <td>00:00</td><td>Spark sees people_1.csv and starts <b>batch 0</b></td></tr> <tr> <td>00:05</td><td>No new files → batch runs, nothing processed</td></tr> <tr> <td>00:10</td><td>Sees people_2.csv and people_3.csv (if they arrived) → <b>batch 1</b> processes them together</td></tr> </tbody> </table>	Time	Action	00:00	Spark sees people_1.csv and starts <b>batch 0</b>	00:05	No new files → batch runs, nothing processed	00:10	Sees people_2.csv and people_3.csv (if they arrived) → <b>batch 1</b> processes them together
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<p>⇒ <b>3 batches for 3 files</b></p> <p>⇒ Latency = <b>as fast as Spark can respond</b></p>	<p>⇒ <b>Only 2 batches for 3 files</b></p> <p>⇒ Latency = <b>bounded by 5-second interval</b></p>																		

## Comparison Table

Feature	Without Trigger	With .trigger(processingTime="5s")
Trigger	Default (as fast as possible)	Fixed 5-second interval
Batch Count	3 batches (1 per file)	2 batches (grouped by time)
Latency	Lower (real-time)	Medium (5s delay max)
Resource Efficiency	High CPU usage per file	More efficient grouping
Control over behavior	No	Yes
Use in Production	Can be noisy / expensive	More predictable

## Summary

- **Without .trigger()** = lower latency, high responsiveness, but may create too many small batches.
- **With .trigger()** = more control, better performance, lower cost at scale.
- Choose based on:
  - **Latency sensitivity** (alerts? dashboards?)
  - **Cost and throughput**
  - **File arrival pattern**

## Final Note:

**Auto Loader** = smart, incremental ingestion from cloud storage with schema management and fault tolerance built-in. It's the recommended way to build the **Bronze layer** in modern data lakehouses using Delta Lake.

Data Processed	Yet to Be Processed
Files that Auto Loader has <b>discovered, read, and successfully written</b> to the target table (e.g., Delta Lake). These are tracked in the <b>checkpoint</b> under commits/, offsets/, and sources/.	Files that are <b>newly arrived</b> in the input directory but <b>haven't been picked up</b> by Auto Loader in any completed micro-batch yet.
<ul style="list-style-type: none"> <li>• Already part of a <b>committed batch</b></li> <li>• Logged in checkpoint metadata</li> <li>• Will <b>not</b> be reprocessed unless:</li> <li>• Checkpoint is deleted/reset</li> <li>• Source is modified manually</li> </ul>	<ul style="list-style-type: none"> <li>• Discovered only if they appear in seenFiles in a future batch</li> <li>• Not yet included in commits/ or offsets/</li> <li>• Will be automatically picked up in the <b>next streaming batch</b></li> </ul>
<i>Example: people_1.csv appears in sources/0 and commits/0 → processed.</i>	<i>Example: people_4.csv was added to the folder after batch 0 completed → will be picked up in batch 1.</i>

## Final Analogy

Term	Think of it as...
Data Processed	Checked in at airport & on the plane
Yet to Be Processed	Still waiting in line at security

Ref: [checkpoint-in-databricks](#)