

SQL Saturday Atlanta 2025 - Al & Bl (#1102)

08 March 2025

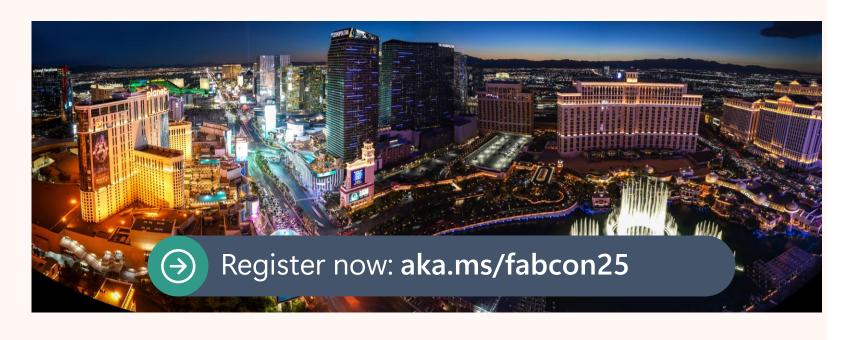
# Fabric Pipelines Metadata-driven ETL Patterns: Mike Diehl Improving Winnipeg

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## Closing Ceremony

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This is where sponsors will give raffle prizes.



## Fabric Pipelines Metadata-driven ETL Patterns



Mike Diehl
Director of Data Engineering and
Business Intelligence

Mike.Diehl@improving.com







## Why use metadata for Fabric Pipelines?

- Reduces ETL development, increases velocity
- Compared to....SSIS
- Lakehouse tables schema evolution (vs SQL database)
- Code and slides:

https://github.com/xhead/SqlSaturdayATL-2025

#### Survey:

- > SQL Server Integration Services
- Azure Data Factory
- Fabric Pipelines

#### Jens Vestergaard

ETL Orchestration: Air Traffic Control for Data

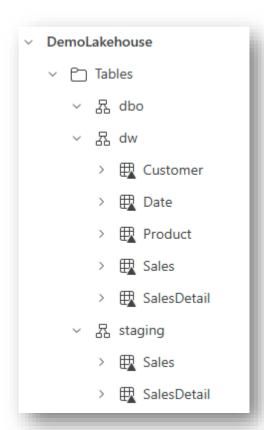
https://t-sql.dk/2025/02/etl-orchestration-air-traffic-control-for-data/



## Scenario: Metadata-driven Approach

#### Target: Lakehouse in OneLake

- Set of tasks:
  - Get data from source
    - Load all data, Overwrite all data
    - Load some data in staging area, merge it into target (incremental)
- Dependencies
  - Load dimensions first, then facts that depend on dimensions
- Develop Pipelines at the Data Source type level
  - SQL server, Oracle server, plus authentication type
  - File source (File System, SharePoint, Azure) and type (XML, JSON, CSV)



## Data Warehouses, Data Lakes, and Data Lakehouses











**Data Warehouse** 

Structured data

- Great for BI
- Quickly becomes expensive at larger data sets

Data Lake

- Unstructured data
- Great for BI and ML/AI
- Better economics for large data sets

Lakehouse

- Both structured and unstructured data in one place
- Blazing-fast
- Great for BI and ML/AI
- Great economics



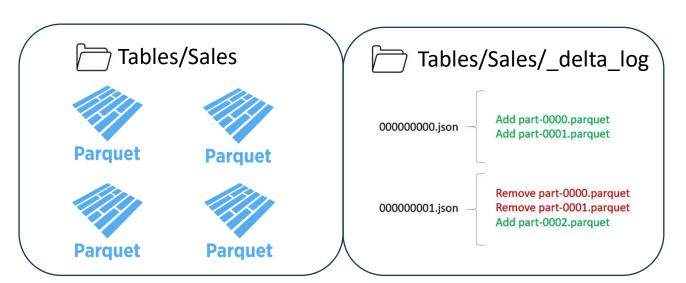


#### **Delta tables**

#### OneLake Lakehouse



- Parquet files
  - Compressed, column-store data
  - Fast queries (like Vertipaq)
- Transaction log (json)
  - Time travel
- Easy schema evolution
- Optimize/vacuum
  - Rewrites/removes parquet files
- Easier/faster to drop/overwrite than to update
  - Unlike RDBMS: use change detection to minimize changes from staging to dw



#### **Viewer Discretion Advised**

These slides may contain screenshots that are disturbing.

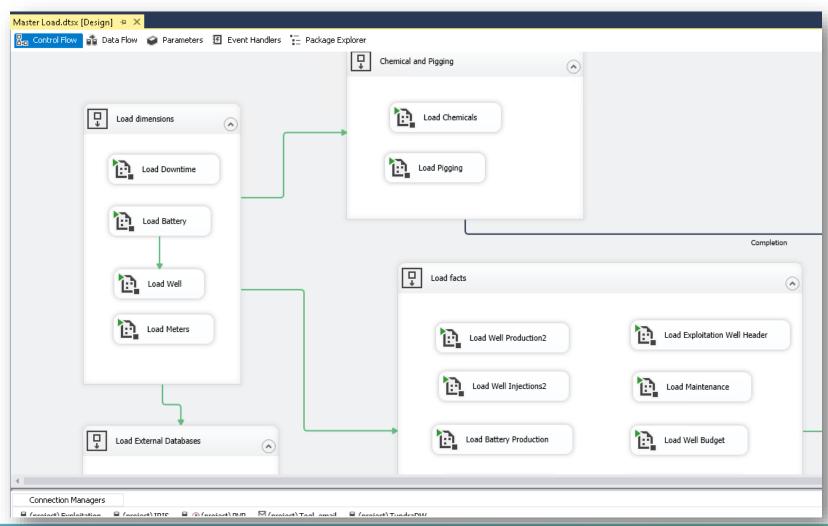
Those that have bad memories of SSIS development may be triggered.



## **SSIS Approach**

#### Develop at the COLUMN Level

- Column changes require updating of mappings in Data flow tasks
- Redeploy updated SSIS packages

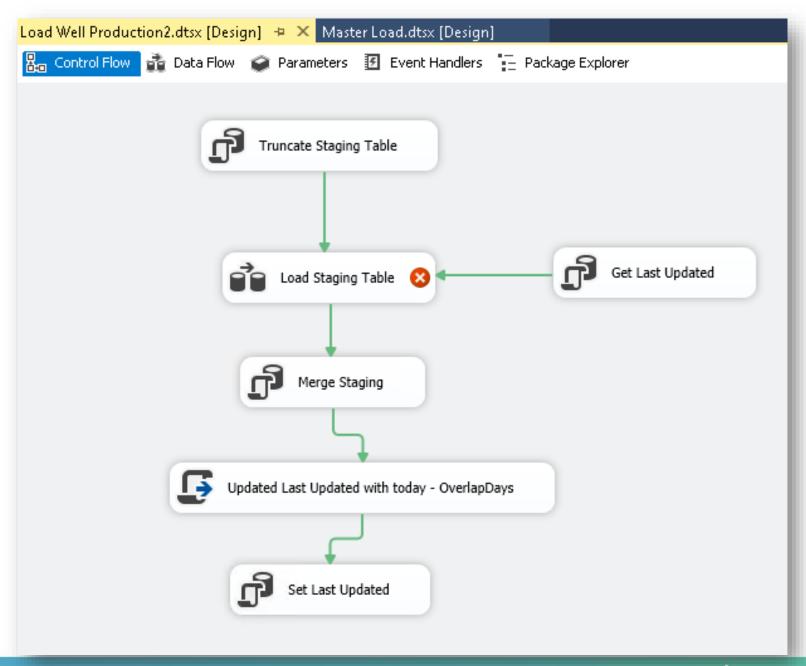




## **SSIS Approach**

Develop at the COLUMN Level

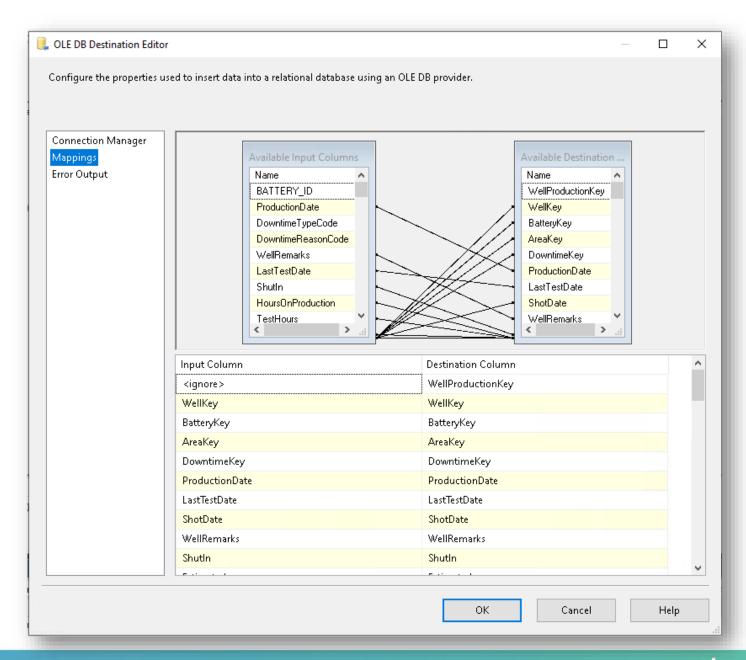
- Column changes require updating of mappings in Data flow tasks
- Redeploy updated SSIS packages



## **SSIS Approach**

Develop at the COLUMN Level

- Column changes require updating of mappings in Data flow tasks
- Redeploy updated SSIS packages



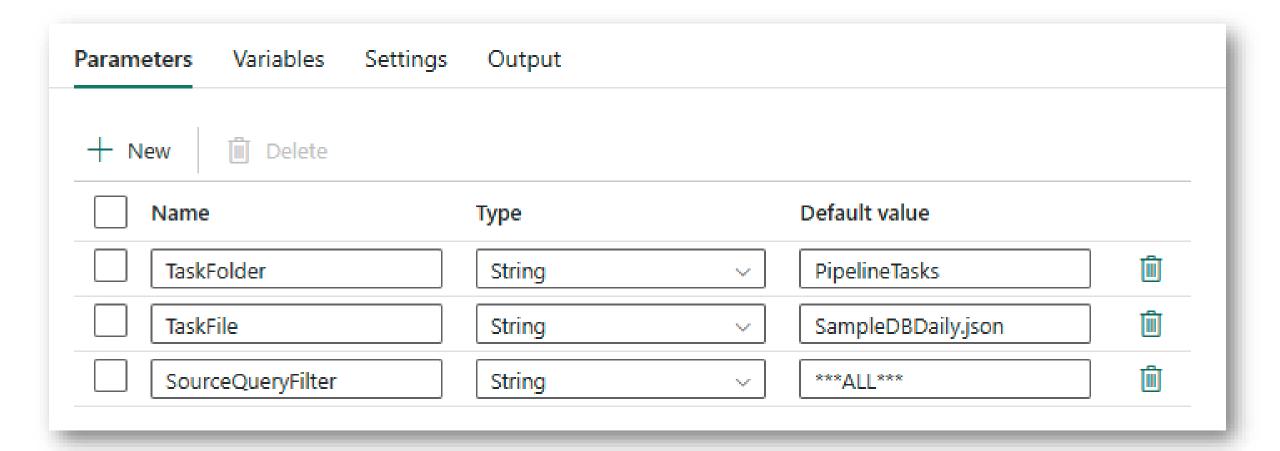


## Advantages of Metadata-driven Approach

ETL Change	SSIS	Deploy SSIS?	Fabric
New data from new source	New data connection, new package or dataflow,	Yes	New service connection, new pipeline, new metadata files
New data from existing source	New package or dataflow	Yes	Add task metadata files
Add/change/drop column in existing source	Refresh column metadata in source & target	Yes	Update task metadata files
Change dependency	Update package	Yes	Update task metadata files, update pipeline (sometimes)
Stop loading existing data	Remove or disable package	Yes	Update task metadata files

## Fabric Pipeline features

**Parameters** 

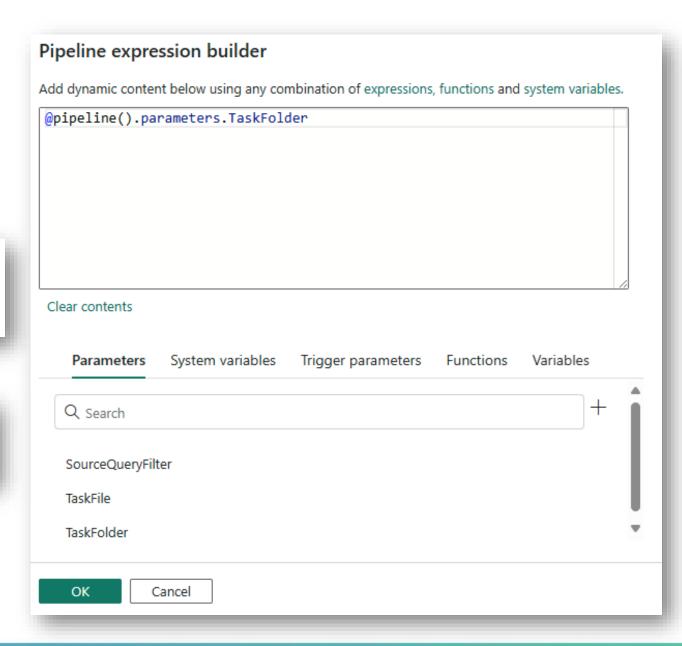


## Fabric Pipeline features

**Dynamic Content** 

Add dynamic content [Alt+Shift+D]

@pipeline().parameters.TaskFolder

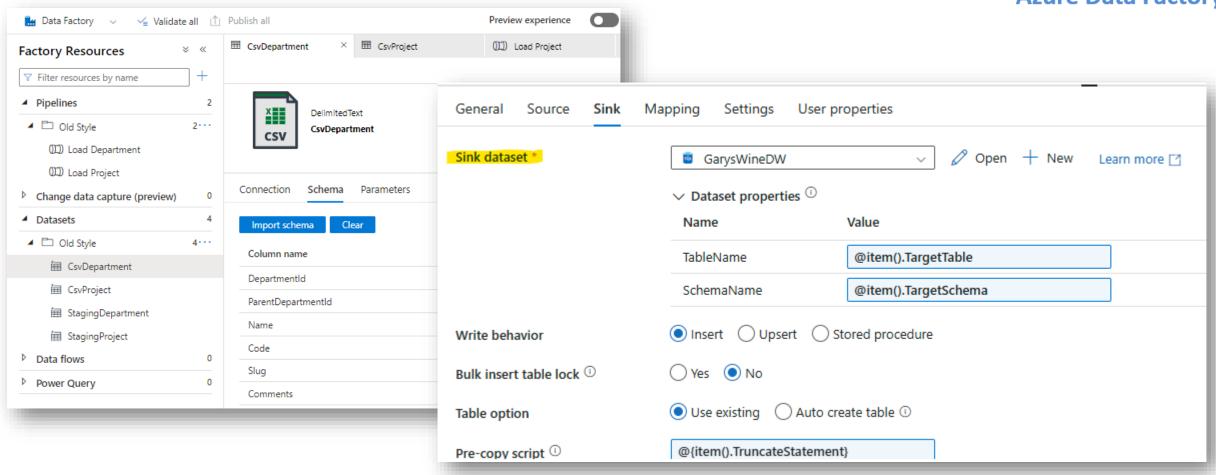




## Azure Data Factory -> Fabric Pipelines

No more Datasets!

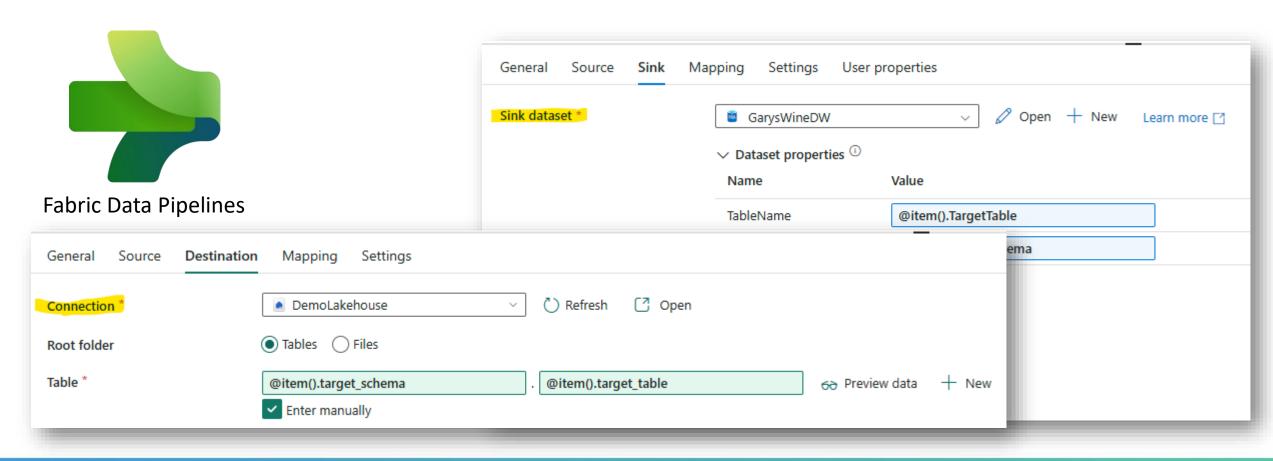




## Azure Data Factory -> Fabric Pipelines

No more Datasets!





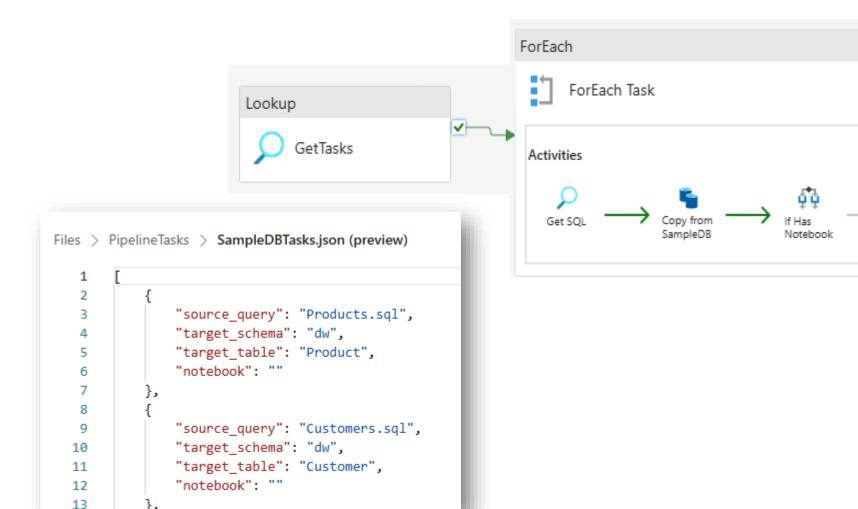
## Typical Metadata-driven Pipeline Pattern



Fabric Pipeline



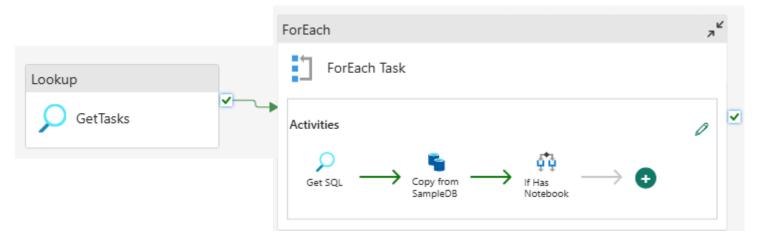
Lakehouse



## Fabric: Typical Pipeline

(per data source type)

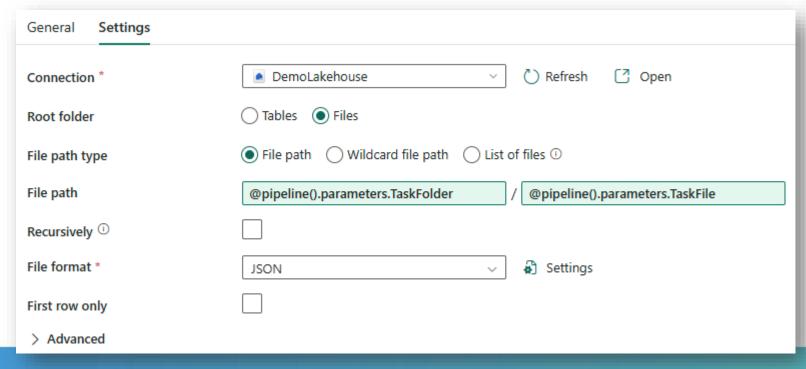
- Get Tasks (Lookup)
  - Gets a json file from Lakehouse files
  - (filter for debug purposes)
- For Each Task
  - Get SQL query from Lakehouse file (Lookup)
  - Copy Data Task
  - Execute Notebook



## Get Tasks (Lookup)

Gets a JSON file from Lakehouse

- Task folder and file name parameters
- Contains JSON array

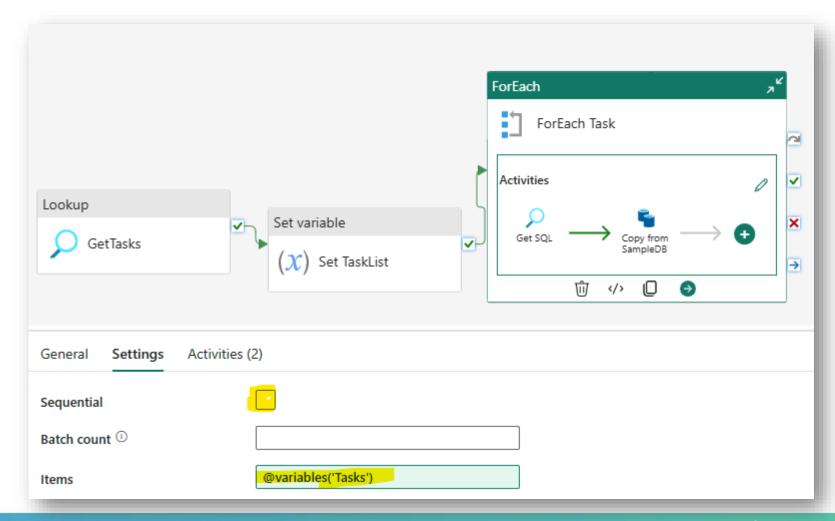


```
Output
 Copy to clipboard
    "count": 5.
    "value": [
              "source_query": "Products.sql",
              "target_schema": "dw",
              "target_table": "Product",
              "notebook": ""
              "source_query": "Customers.sql",
              "target_schema": "dw",
              "target table": "Customer",
              "notebook": ""
              "source_query": "Date.sql",
              "target_schema": "dw",
              "target_table": "Date"
              "source_query": "CurrentYearSales.sql",
              "target_schema": "staging",
              "target_table": "Sales",
              "notebook": "MergeSales"
              "source_query": "CurrentYearSalesDetails.sql",
              "target_schema": "staging",
              "target_table": "SalesDetail",
              "notebook": "MergeSalesDetail"
```

#### For Each Task

Iterates through item array

- Output of GetTasks
- Item() object
- Parallel or serial execution

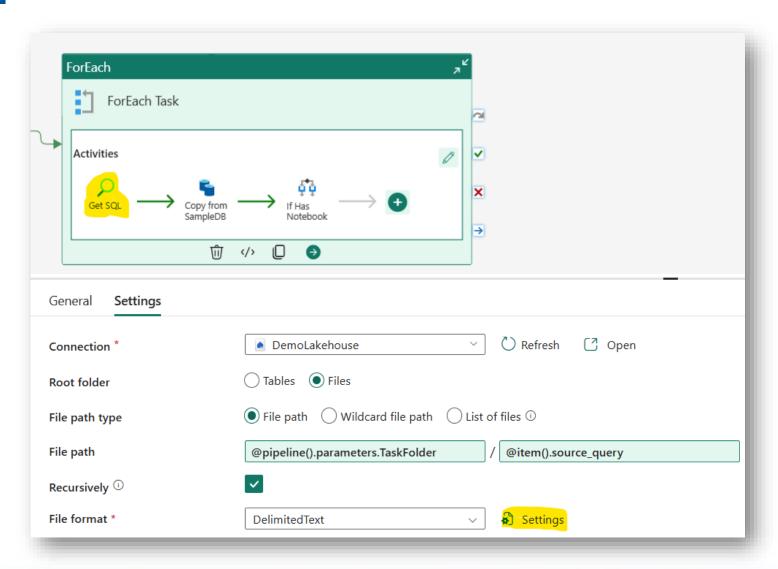




## For Each - Read SQL

Lookup task to get query text

- Read file as DelimitedText
- Set delimiters so only one row, one column is found
- No Header

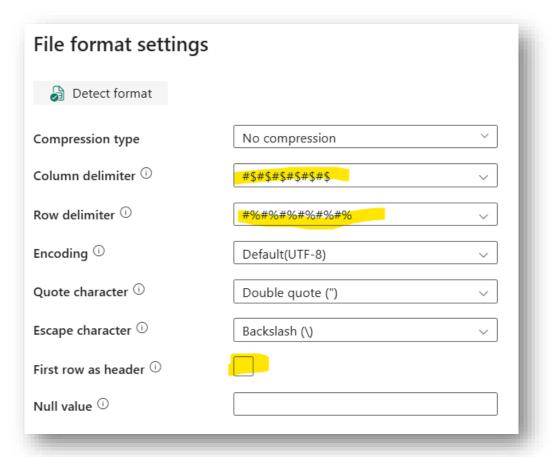




## For Each - Read SQL

Lookup task to get query text

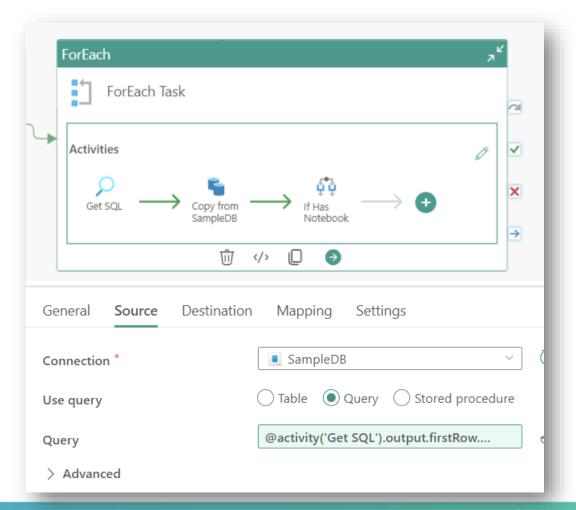
- Read file as DelimitedText
- Set delimiters so only one row, one column is found
- No Header



## For Each – Copy Data Task

#### Source

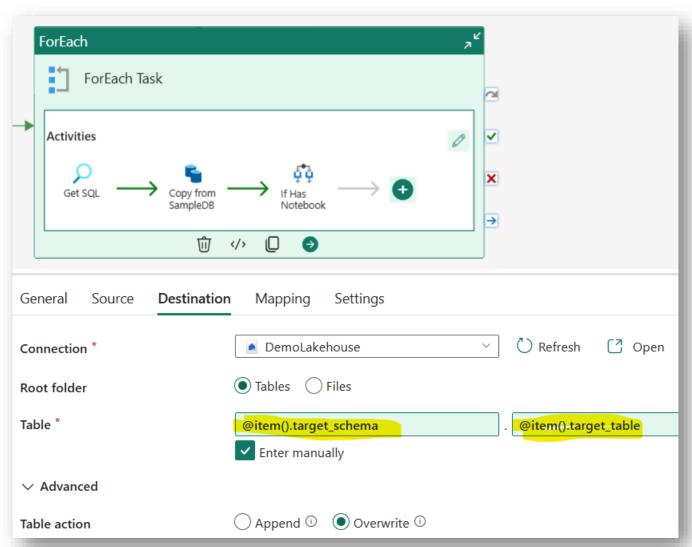
- Dynamic property for Source Query
- @activity('Get SQL').output
   .firstRow.prop\_0



## For Each - Copy Data Task

#### **Destination**

- Dynamic properties for Target Schema & Table
- Overwrite
- Target table may not exist
  - But schema needs to exist

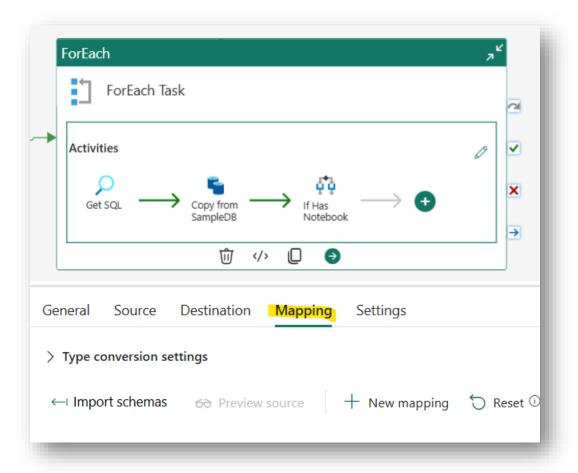




## For Each - Copy Data Task

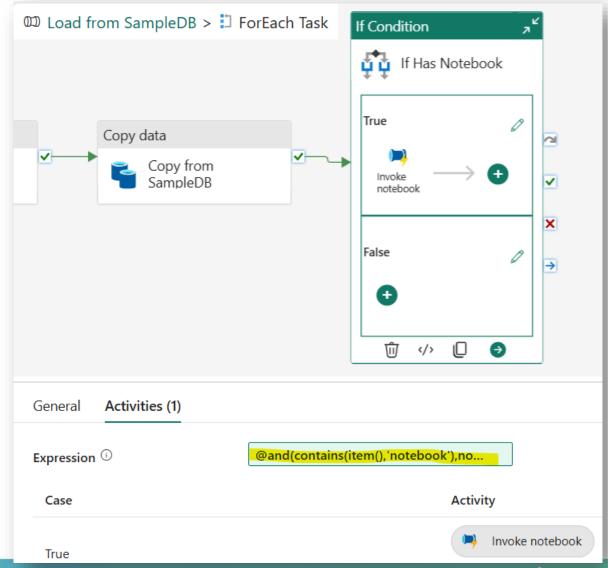
Mapping

 Zero column mapping (very different from SSIS)



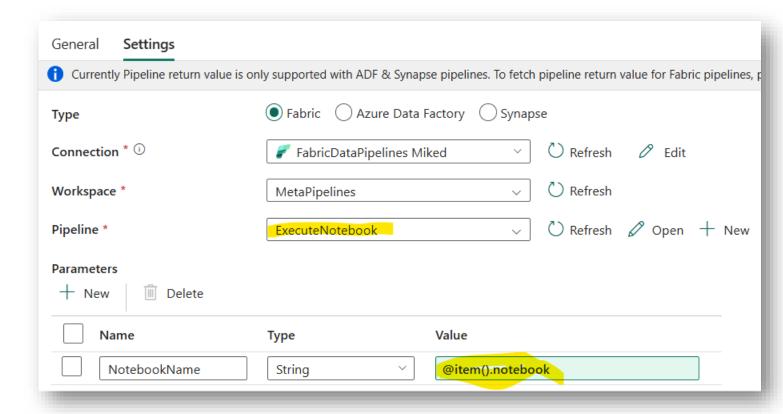
#### For Each - Execute notebook

- Execute notebook to process staging data
- @and(contains(item(),'notebook'),
  not(empty(item().notebook)))



#### For Each - Execute notebook

 Calls another pipeline to execute the notebook





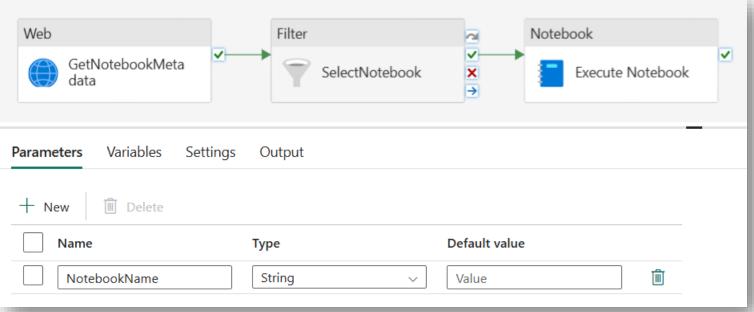
#### For Each – Execute notebook

Invoke Notebook pipeline

 Need the resource ID of the notebook, not the name

REST API gets all notebook metadata

- Filter selects by name
- Dynamic properties for notebook execution task





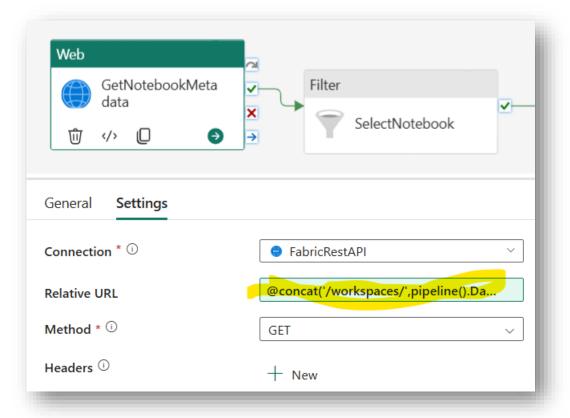
#### For Each - Execute notebook

Invoke Notebook pipeline

- Need the resource ID of the notebook, not the name
- REST API gets all notebook metadata
- Base URL: <a href="https://api.fabric.microsoft.com/v1/">https://api.fabric.microsoft.com/v1/</a>
- Relative URL:

```
@concat('/workspaces/',pipeline()
.DataFactory,'/items?type=Notebook')
```

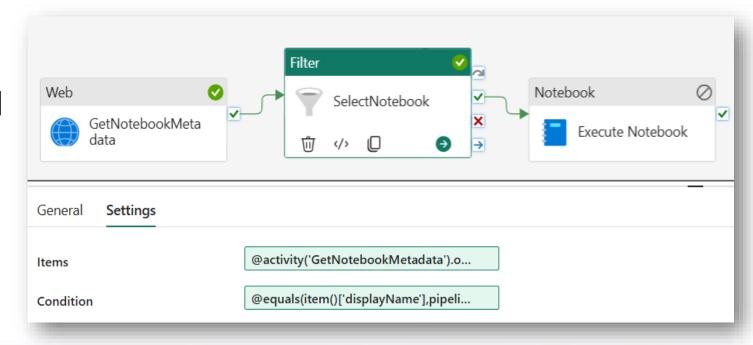
• (all notebooks in this workspace)



#### For Each – Execute notebook

Invoke Notebook pipeline

- Filter selects by name
- Items: @activity( 'GetNotebookMetadata') .output.value
- Condition:@equals(item()['displayName'],pipeline().parameters
  - .NotebookName)

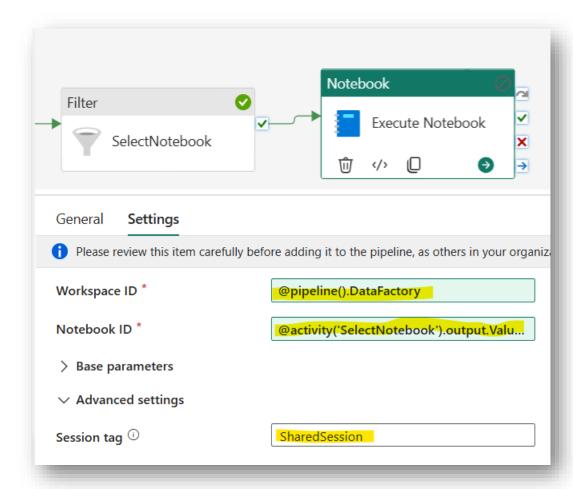




#### For Each - Execute notebook

#### Invoke Notebook pipeline

- Notebook ID:
   @activity('SelectNotebook')
   .output.Value[0].id
- Session tag



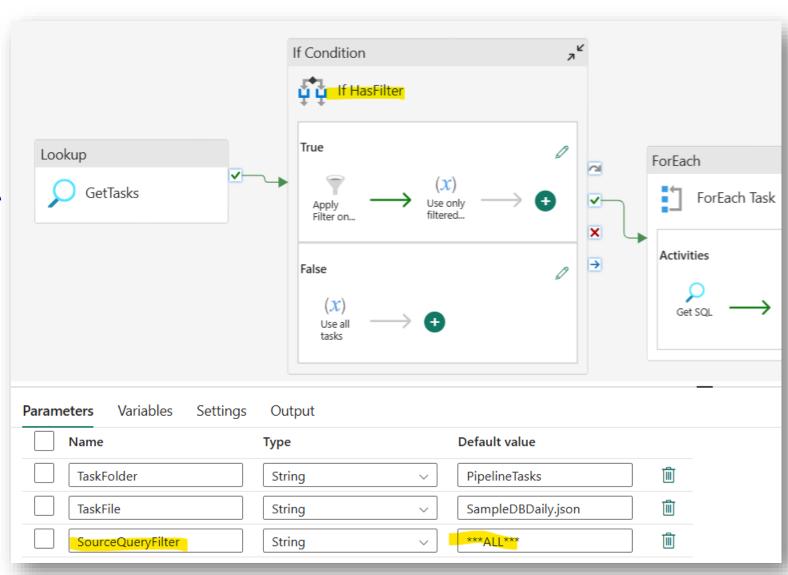


## **Debugging tasks**

Filter by task name

If HasFilter:

```
@not(equals(pipeline()
.parameters.SourceQueryFilter
,'***ALL***'))
```

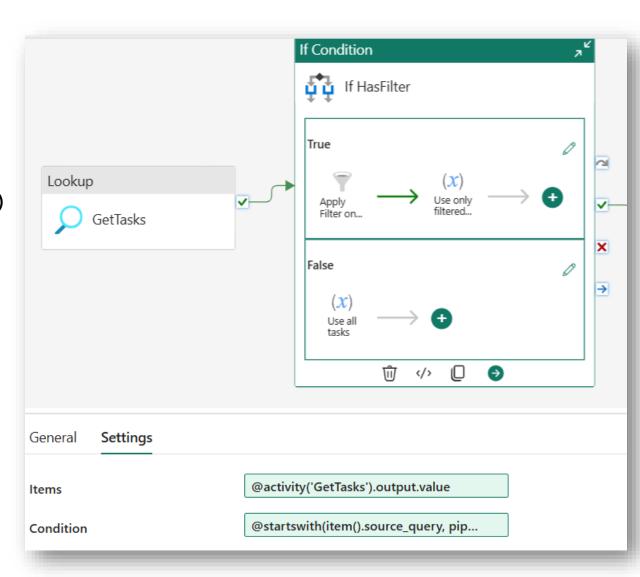




## **Debugging tasks**

Filter by task name

- Filter Condition:
   @startswith(item().source\_query
  ,pipeline().parameters.SourceQueryFilter)
- Set tasks variable





## **How Many Pipelines?**

- Usually One per Data Source, plus one Main pipeline
- Most pipelines use the Lookup/ForEach/Copy Data/Exec notebook pattern

## **Main Pipeline**

- Calls Task-driven pipelines with parameter for task file
- Main pipeline handles dependencies

"Level 1" pipelines – loading dimensions

"Level 2" pipelines – loading facts

Additional levels as needed, based on dependency tree

- Advanced: Main pipeline can use the Lookup/ForEach pattern to get a list of pipelines (and their parameters) to execute
- Could arrange pipelines in medallion order



#### **Notebooks**

#### Incremental loading

- Staging table contains complete data for a range of dates
  - CurrentYearSales.sql (from Jan 1 of this year)
  - PastYearSales.sql (before Jan 1 of this year)
- Notebook: MergeSales

```
%run CommonLakehouseMerge
MergeByDateRange("staging.Sales", "dw.Sales", "OrderDate")
```

1 def MergeByDateRange(staging\_table, target\_table, date\_range\_replace\_column):

#### **Notebooks**

#### Incremental loading

- Staging table contains data identified by natural key
  - CurrentYearSalesDetails.sql (no Order Date)
- Notebook: MergeSalesDetails

```
%run CommonLakehouseMerge
MergeUpsert("staging.SalesDetail", "dw.SaleDetail",
"SalesOrderID")
```

```
def MergeUpsert(staging_table, target_table, key_column):
```

## CommonLakehouseMerge

#### MergeByDateRange

- Check that target table exists
- Gets Min and Max values
- Builds ReplaceWhere clause
- Merge Schema

```
def MergeByDateRange(staging table, target table, date range replace column):
         target df = spark.sql(f"select * from {target table}")
3
         source df = spark.sql(f"select * from {staging table}")
         #check if table has any columns or has already columns but they are empty
         if len(target df.columns)==0 or target df.isEmpty():
             # first time insert when nothing to delete
             (source df
             .write
             .format("delta")
11
12
             .mode("overwrite")
             .option("mergeSchema", "true")
13
             .saveAsTable(target table)
14
15
         else:
16
17
             # insert with replacement by 'date range replace column'
             min date = source df.agg(min(col(date range replace column))).collect()[0][0]
18
             max date = source df.agg(max(col(date range replace column))).collect()[0][0]
             replace where = f"`{date range replace column}` between '{min date}' and '{max date}'"
20
             (source df
21
22
             .write
             .format("delta")
23
             .mode("overwrite")
24
             .option("replaceWhere", replace where)
25
             .option("mergeSchema", "true")
26
27
             .saveAsTable(target table)
28
```

## CommonLakehouseMerge

#### MergeUpsert

- Opens native
   DeltaTable from
   Lakehouse path
- Merge with match clause
- Match update
- No match insert
- Schema evolution

```
def MergeUpsert(staging table, target table, key column):
         #read from delta tables to spark dataframes
         target df = spark.sql(f"select * from {target table}")
         source df = spark.sql(f"select * from {staging table}")
         #check if table has any columns or has already columns but they are empty
         if len(target df.columns)==0 or target df.isEmpty():
8
16
         else:
17
             #read DeltaTable from Lakehouse path
18
             lakehouse table path = f"{get lakehouse path()}/Tables/{target table.replace('.','/')}"
19
             target dt = DeltaTable.forPath(spark, lakehouse table path)
20
21
22
             # Alias the columns to avoid name conflicts
23
             target dt = target dt.alias("target")
             source df = source df.alias("source")
24
25
             (target dt
26
                  .merge(source df, f"source.`{key column}` = target.`{key column}`")
27
                  .whenMatchedUpdateAll()
28
                  .whenNotMatchedInsertAll()
29
                 # .whenNotMatchedBySourceDelete()
30
                  .withSchemaEvolution()
31
32
                  .execute()
33
```

## Demo

## Changing ETL Requirements

New table in target from same source?

Add Staging and dw tables,
Add an item to task file
Add query file
No pipeline changes required
Merge Notebook (maybe)

Change in target table? (Add column, remove column, change column)

Change Staging and dw tables, Update query file Merge Notebook (maybe)

Incorrect logic in SourceQuery?

Update query file

Target table no longer needed?

Remove item from task file



## Advantages of Metadata-driven Approach

ETL Change	SSIS	Deploy SSIS?	Fabric
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Stop loading existing data	Remove or disable package	Yes	Update task metadata files





## Code and slides:

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