# Integrate SQL and Spark pools in Azure Synapse Analytics

**Note:**

You are not required to complete the processes, tasks, activities, or steps presented in this example. The various samples provided are for illustrative purposes only and it's likely that if you try this out you will encounter issues in your system.

Here, we explore integrating SQL and Apache Spark pools in Azure Synapse Analytics.

## Integrating SQL and Apache Spark pools in Azure Synapse Analytics

You want to write to a dedicated SQL pool after performing data engineering tasks in Spark, then reference the SQL pool data as a source for joining with Apache Spark DataFrames that contain data from other files.

You decide to use the Azure Synapse Apache Spark to Synapse SQL connector to efficiently transfer data between Spark pools and SQL pools in Azure Synapse.

Transferring data between Apache Spark pools and SQL pools can be done using JavaDataBaseConnectivity (JDBC). However, given two distributed systems such as Apache Spark and SQL pools, JDBC tends to be a bottleneck with serial data transfer.

The Azure Synapse Apache Spark pool to Synapse SQL connector is a data source implementation for Apache Spark. It uses the Azure Data Lake Storage Gen2 and PolyBase in SQL pools to efficiently transfer data between the Spark cluster and the Synapse SQL instance.

1. If we want to use the Apache Spark pool to Synapse SQL connector (**`sqlanalytics`**), one option is to create a temporary view of the data within the DataFrame. Execute the code below in a new cell to create a view named **`top_purchases`**:

```
1
2
```

```
# Create a temporary view for top purchases
topPurchases.createOrReplaceTempView("top_purchases")
```

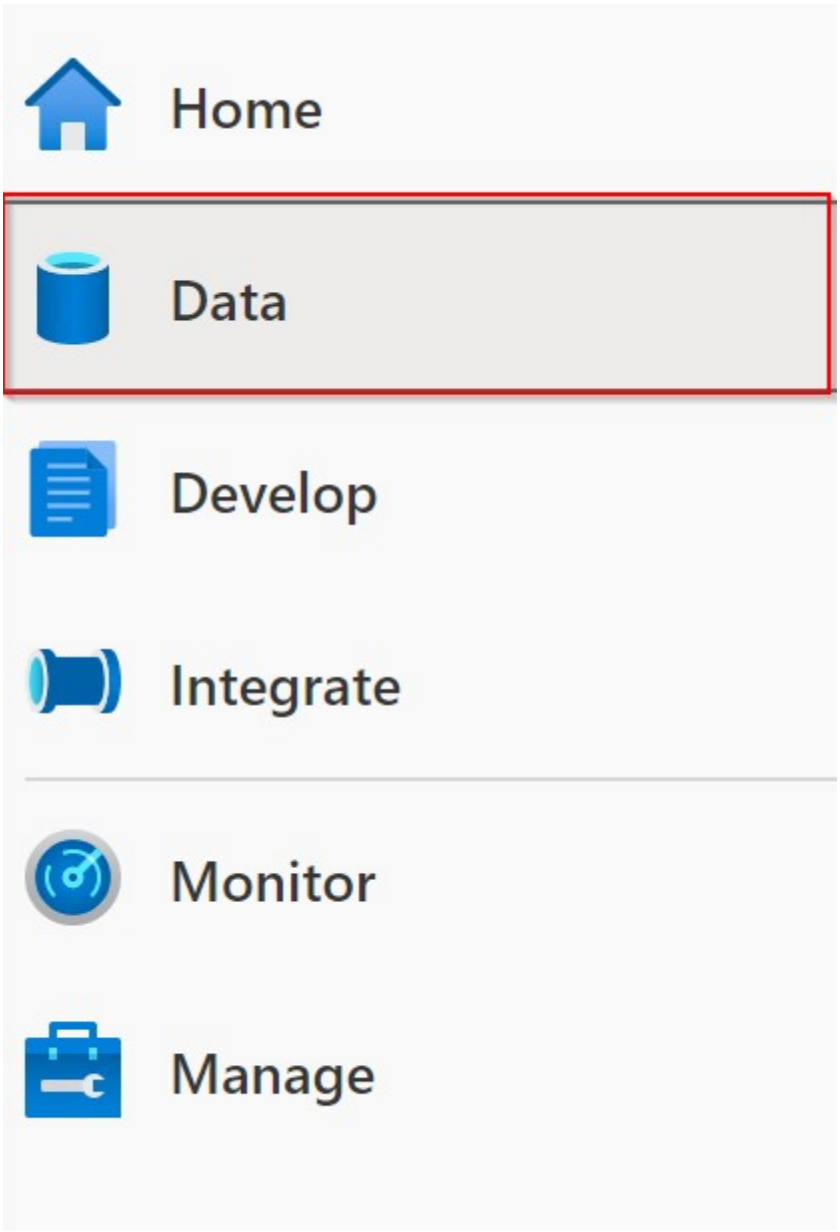
We created a new temporary view from the **`topPurchases`** dataframe that we created earlier and which contains the flattened JSON user purchases data.

2. We must execute code that uses the Apache Spark pool to Synapse SQL connector in Scala. To do so, we add the **`%%spark`** magic to the cell. Execute the code below in a new cell to read from the **`top_purchases`** view:

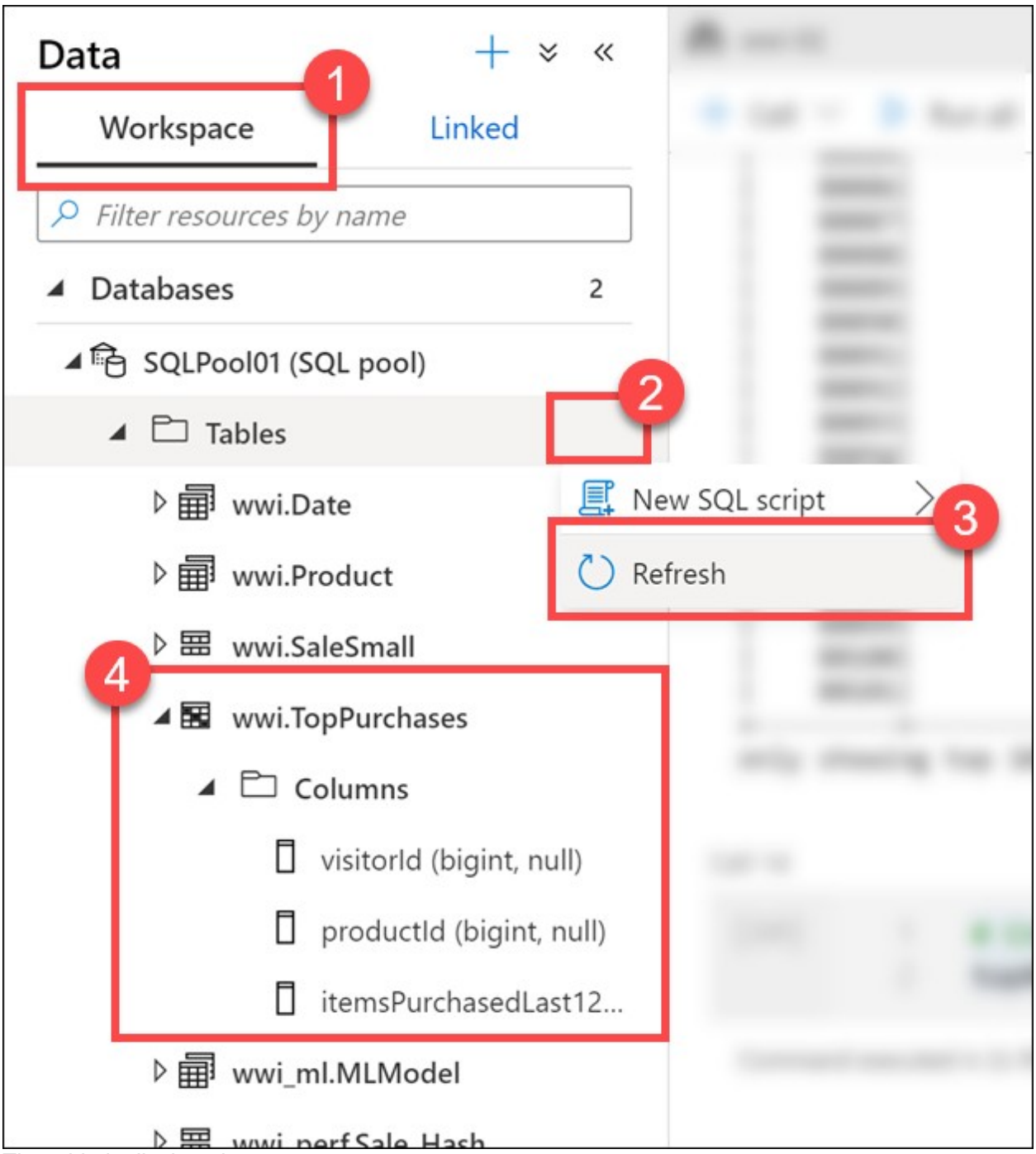
```
%%spark
// Make sure the name of the SQL pool (SQLPool01 below) matches the name of your SQL pool.
val df = spark.sqlContext.sql("select * from top_purchases")
df.write.sqlanalytics("SQLPool01.wwi.TopPurchases", Constants.INTERNAL)
```

**Note:** The cell may take over a minute to execute. If you have run this command before, you will receive an error stating that "There is already and object named..." because the table already exists.

After the cell finishes executing, let's take a look at the list of SQL pool tables to verify that the table was successfully created for us. 3. **Leave the notebook open**, then navigate to the **Data** hub (if not already selected).




4. Select the **Workspace** tab **(1)**, expand the SQL pool, select the **ellipses (...)** on Tables **(2)** and select Refresh **(3)**. Expand the **`wwi.TopPurchases`** table and columns **(4)**.

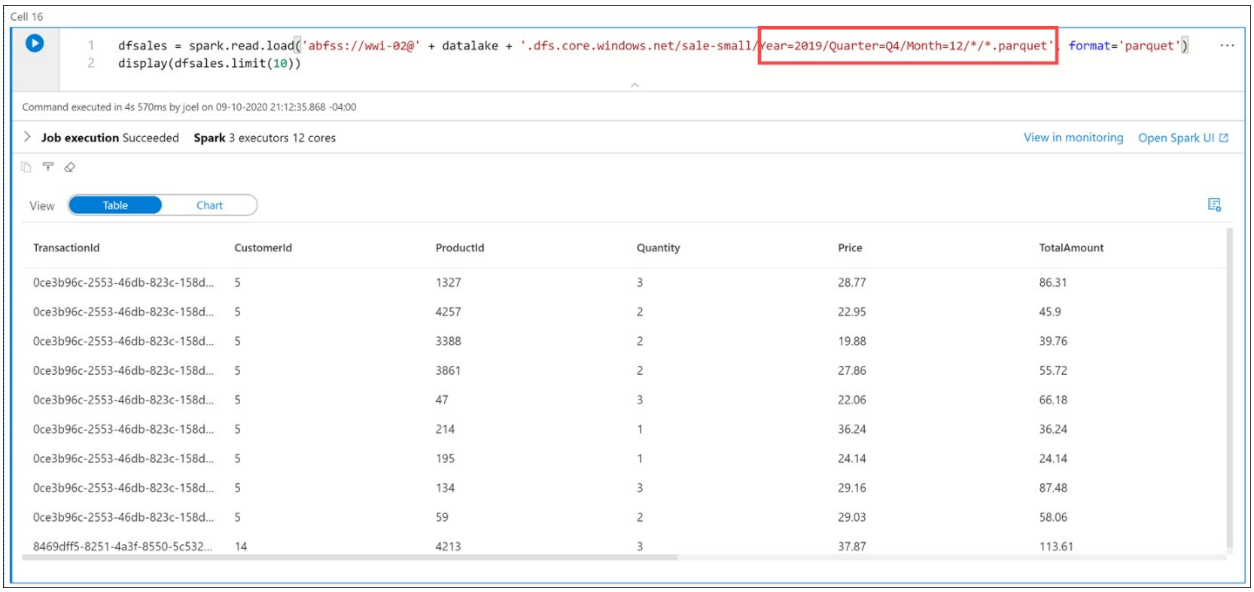



The table is displayed

As you can see, the **`wwi.TopPurchases`** table was automatically created for us, based on the derived schema of the Apache Spark DataFrame. The Apache Spark pool to Synapse SQL connector was responsible for creating the table and efficiently loading the data into it. 5. Return to the notebook and execute the code below in a new cell to read sales data from all the Parquet files located in the **`sale-small/Year=2019/Quarter=Q4/Month=12/`** folder:

```
dfsales = spark.read.load('abfss://wwi-02@' + datalake + '.dfs.core.windows.net/
sale-small/Year=2019/Quarter=Q4/Month=12/*/*.parquet', format='parquet')
display(dfsales.limit(10))
```

**Note:** It can take over 3 minutes for this cell to execute. The **`datalake`** variable we created in the first cell is used here as part of the file path.




| TransactionId | CustomerId | ProductId | Quantity | Price | TotalAmount |
|---|---|---|---|---|---|
| 0ce3b96c-2553-46db-823c-158d... | 5 | 1327 | 3 | 28.77 | 86.31 |
| 0ce3b96c-2553-46db-823c-158d... | 5 | 4257 | 2 | 22.95 | 45.9 |
| 0ce3b96c-2553-46db-823c-158d... | 5 | 3388 | 2 | 19.88 | 39.76 |
| 0ce3b96c-2553-46db-823c-158d... | 5 | 3861 | 2 | 27.86 | 55.72 |
| 0ce3b96c-2553-46db-823c-158d... | 5 | 47 | 3 | 22.06 | 66.18 |
| 0ce3b96c-2553-46db-823c-158d... | 5 | 214 | 1 | 36.24 | 36.24 |
| 0ce3b96c-2553-46db-823c-158d... | 5 | 195 | 1 | 24.14 | 24.14 |
| 0ce3b96c-2553-46db-823c-158d... | 5 | 134 | 3 | 29.16 | 87.48 |
| 0ce3b96c-2553-46db-823c-158d... | 5 | 59 | 2 | 29.03 | 58.06 |
| 8469dff5-8251-4a3f-8550-5c532... | 14 | 4213 | 3 | 37.87 | 113.61 |

The cell output is displayed
Compare the file path in the cell above to the file path in the first cell. Here we are using a relative path to load all **December 2019 sales** data from the Parquet files located in **`sale-small`**, versus just December 31, 2010 sales data.

Next, let's load the **`TopSales`** data from the SQL pool table we created earlier into a new Apache Spark DataFrame, then join it with this new **`dfsales`** DataFrame.

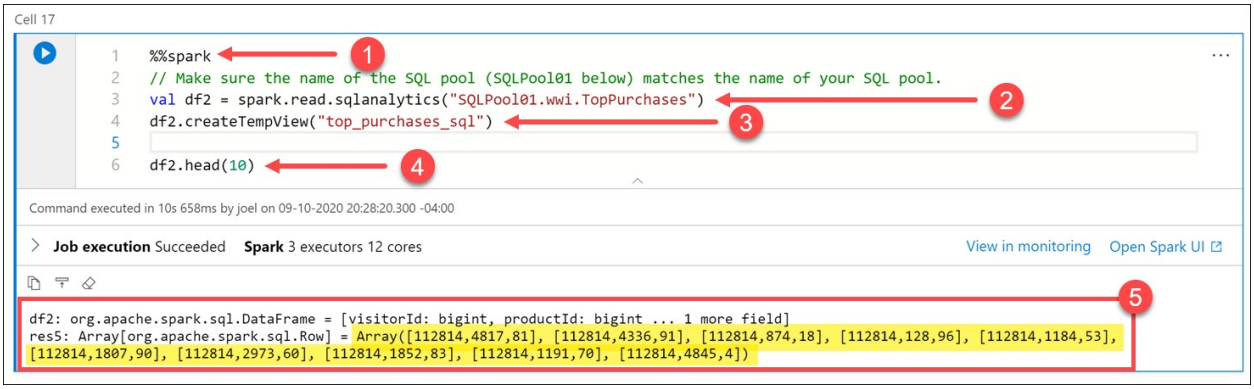
To do so, we must once again use the **`%%spark`** magic on a new cell since we'll use the Apache Spark pool to Synapse SQL connector to retrieve data from the SQL pool. Then we need to add the DataFrame contents to a new temporary view so we can access the data from Python.

6. Execute the code below in a new cell to read from the **`TopSales SQL`** pool table and save it to a temporary view:

```
%%spark
// Make sure the name of the SQL pool (SQLPool01 below) matches the name of your
SQL pool.
```

```
val df2 = spark.read.sqlanalytics("SQLPool01.wwi.TopPurchases")
df2.createTempView("top_purchases_sql")

df2.head(10)
```




The cell and its output are displayed as described.
The cell's language is set to **`Scala`** by using the **`%%spark`** magic **(1)** at the top of the cell. We declared a new variable named **`df2`** as a new DataFrame created by the **`spark.read.sqlanalytics`** method, which reads from the **`TopPurchases`** table **(2)** in the SQL pool.

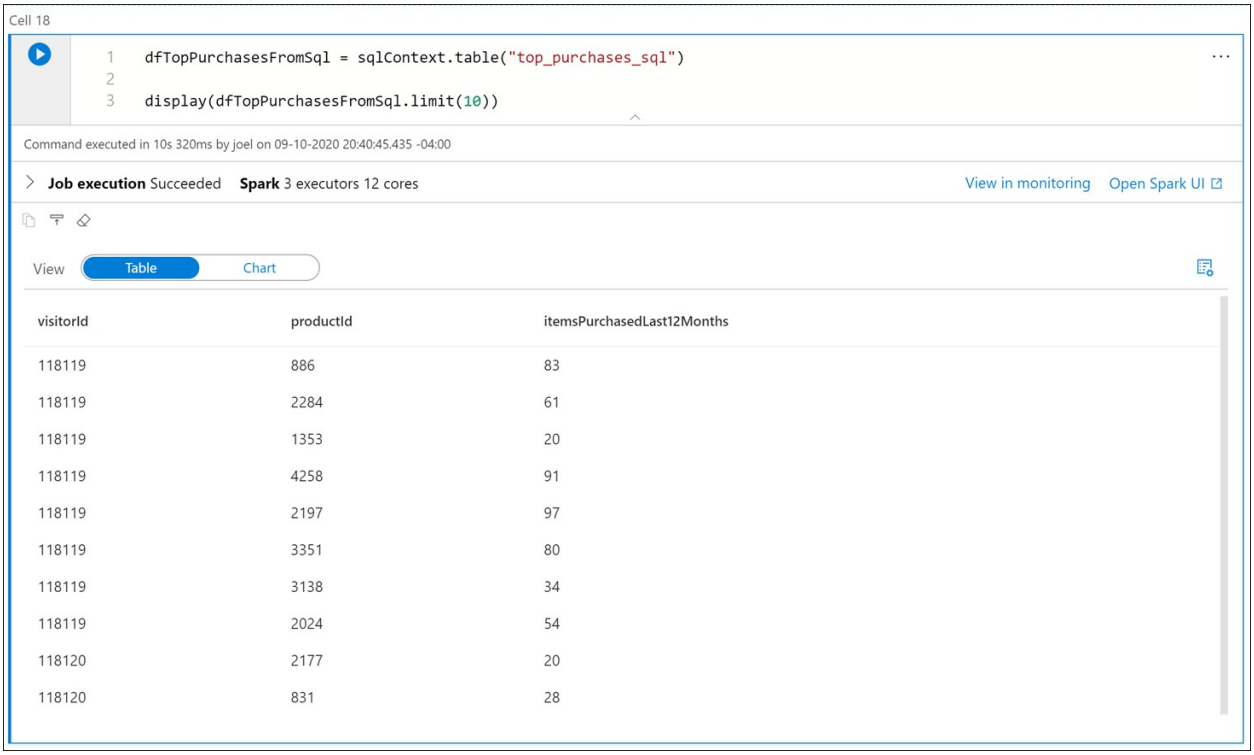
Then we populated a new temporary view named **`top_purchases_sql`** **(3)**.

Finally, we showed the first 10 records with the **`df2.head(10))`** line **(4)**. The cell output displays the DataFrame values **(5)**. 7. Execute the code below in a new cell to create a new DataFrame in Python from the **`top_purchases_sql`** temporary view, then display the first 10 results:

```
1
2
3
```

```
dfTopPurchasesFromSql = sqlContext.table("top_purchases_sql")

display(dfTopPurchasesFromSql.limit(10))
```




The DataFrame code and output are displayed.

8. Execute the code below in a new cell to join the data from the sales Parquet files and the **`TopPurchases`** SQL pool:

```
inner_join = dfsales.join(dfTopPurchasesFromSql,
    (dfsales.CustomerId == dfTopPurchasesFromSql.visitorId) & (dfsales.ProductId
== dfTopPurchasesFromSql.productId))

inner_join_agg = (inner_join.select("CustomerId","TotalAmount","Quantity","itemsP
urchasedLast12Months","top_purchases_sql.productId")
    .groupBy(["CustomerId","top_purchases_sql.productId"])
    .agg(
        sum("TotalAmount").alias("TotalAmountDecember"),
        sum("Quantity").alias("TotalQuantityDecember"),
```

```
        sum("itemsPurchasedLast12Months").alias("TotalItemsPurchasedLast12Months
"))
    .orderBy("CustomerId") )

display(inner_join_agg.limit(100))
```

In the query, we joined the **`dfsales`** and **`dfTopPurchasesFromSql`** DataFrames, matching on **`CustomerId`** and **`ProductId`**. This join combined the **`TopPurchases`** SQL pool table data with the December 2019 sales Parquet data **(1)**.

We grouped by the **`CustomerId`** and **`ProductId`** fields. Since the **`ProductId`** field name is ambiguous (it exists in both DataFrames), we had to fully qualify the **`ProductId`** name to refer to the one in the **`TopPurchases`** DataFrame **(2)**.

Then we created an aggregate that summed the total amount spent on each product in December, the total number of product items in December, and the total product items purchased in the last 12 months **(3)**.

Finally, we displayed the joined and aggregated data in a table view.

Feel free to select the column headers in the Table view to sort the result set.