



```
display(dbutils.fs.ls("abfss://prj2@dbricksprj.dfs.core.windows.net/"))
```



	A <sub>C</sub> path	A <sub>C</sub> name	1 <sub>3</sub> size	1 <sub>3</sub> modificationTime
1	abfss://prj2@dbricksprj.dfs.core.windows.net/bronze/	bronze/	0	1758879204000
2	abfss://prj2@dbricksprj.dfs.core.windows.net/csvfile...	csvfiles/	0	1758864466000
3	abfss://prj2@dbricksprj.dfs.core.windows.net/gold/	gold/	0	1758864490000
4	abfss://prj2@dbricksprj.dfs.core.windows.net/silver/	silver/	0	1758864479000

4 rows

```
spark.read.parquet('abfss://prj2@dbricksprj.dfs.core.windows.net/bronze').display()
```



A <sub>C</sub> TransactionID	A <sub>C</sub> CustomerID	1 <sub>3</sub> CustomerAge	A <sub>C</sub> Gender	A <sub>C</sub> ProductID	A <sub>C</sub> ProductName
------------------------------	---------------------------	----------------------------	-----------------------	--------------------------	----------------------------

100 rows

```
from pyspark.sql.functions import col, upper, trim, when;
```

```
bronze_df=spark.read.parquet('abfss://prj2@dbricksprj.dfs.core.windows.net/bronze')
display(bronze_df)
```

```
bronze_df: pyspark.sql.connect.dataframe.DataFrame = [TransactionID: string, CustomerID: string ... 18 more fields]
```

Q            

	TransactionID	CustomerID	CustomerAge	Gender	ProductID	ProductName
1	TXN10000	C1000	null	Male	P600	Pepsi Decor
2	TXN10001	C1001	54	Female	P601	Nestle Beverages
3	TXN10002	C1002	null	Male	P602	Arrow Decor
4	TXN10003	C1003	null	Male	P603	Nestle Snacks
5	TXN10004	C1004	48	Male	P604	Sony Beverages
6	TXN10005	C1005	null	Female	P605	Nestle Snacks
7	TXN10006	C1006	59	Female	P606	Pepsi Furniture
8	TXN10007	C1007	58	Female	P607	Nestle Snacks
9	TXN10008	C1008	20	Female	P608	Levis Laptops
10	TXN10009	C1009	33	Female	P609	Nestle Shirts
11	TXN10010	C1010	null	Female	P610	Apple Snacks
12	TXN10011	C1011	20	Female	P611	Nestle Snacks
13	TXN10012	C1012	null	Male	P612	Apple Decor
14	TXN10013	C1013	null	Male	P613	Arrow Snacks

100 rows

```
df_clean1 = bronze_df.filter(
  (col("TransactionID").isNotNull()) &
  (col("CustomerID").isNotNull()) &
  (col("TransactionDate").isNotNull())
)
display(df_clean1)
```

df\_clean1: pyspark.sql.connect.dataframe.DataFrame = [TransactionID: string, CustomerID: string ... 18 more fields]

Table



	TransactionID	CustomerID	CustomerAge	Gender	ProductID	ProductName
1						
2						
3						
4						
5						
6						
7						
8						
9						
10						
11						
12						
13						
14						
15						

100 rows

```
# Step 3: Trim and standardize text fields
df_clean2 = df_clean1.withColumn("PaymentType", upper(trim(col("PaymentType")))) \
  .withColumn("StoreRegion", upper(trim(col("StoreRegion")))) \
  .withColumn("DeviceUsed", upper(trim(col("DeviceUsed"))))

display(df_clean2)
```

df\_clean2: pyspark.sql.connect.dataframe.DataFrame = [TransactionID: string, CustomerID: string ... 18 more fields]

Table							🔍 ⚙️ 📄 🗑️
	TransactionID	CustomerID	CustomerAge	Gender	ProductID	ProductName	▲
1	TXN10000	C1000	null	Male	P600	Pepsi Decor	⌵
2	TXN10001	C1001	54	Female	P601	Nestle Beverages	
3	TXN10002	C1002	null	Male	P602	Arrow Decor	
4	TXN10003	C1003	null	Male	P603	Nestle Snacks	
5	TXN10004	C1004	48	Male	P604	Sony Beverages	
6	TXN10005	C1005	null	Female	P605	Nestle Snacks	
7	TXN10006	C1006	59	Female	P606	Pepsi Furniture	
8	TXN10007	C1007	58	Female	P607	Nestle Snacks	
9	TXN10008	C1008	20	Female	P608	Levis Laptops	
10	TXN10009	C1009	33	Female	P609	Nestle Shirts	
11	TXN10010	C1010	null	Female	P610	Apple Snacks	
12	TXN10011	C1011	20	Female	P611	Nestle Snacks	
13	TXN10012	C1012	null	Male	P612	Apple Decor	
14	TXN10013	C1013	null	Male	P613	Arrow Snacks	
15							▶

100 rows

```
df_clean3 = df_clean2.withColumn("TransactionDate", col("TransactionDate").cast("timestamp")) \
    .withColumn("Quantity", col("Quantity").cast("int")) \
    .withColumn("Amount", col("Amount").cast("float")) \
    .withColumn("Discount", col("Discount").cast("float"))

display(df_clean3)
```

df\_clean3: pyspark.sql.connect.dataframe.DataFrame = [TransactionID: string, CustomerID: string ... 18 more fields]

Table							🔍 ⚙️ 📄 🗑️
	TransactionID	CustomerID	CustomerAge	Gender	ProductID	ProductName	▲
1	TXN10000	C1000	null	Male	P600	Pepsi Decor	⌵
2	TXN10001	C1001	54	Female	P601	Nestle Beverages	
3	TXN10002	C1002	null	Male	P602	Arrow Decor	
4	TXN10003	C1003	null	Male	P603	Nestle Snacks	
5	TXN10004	C1004	48	Male	P604	Sony Beverages	
6	TXN10005	C1005	null	Female	P605	Nestle Snacks	
7	TXN10006	C1006	59	Female	P606	Pepsi Furniture	
8	TXN10007	C1007	58	Female	P607	Nestle Snacks	
9	TXN10008	C1008	20	Female	P608	Levis Laptops	
10	TXN10009	C1009	33	Female	P609	Nestle Shirts	
11	TXN10010	C1010	null	Female	P610	Apple Snacks	
12	TXN10011	C1011	20	Female	P611	Nestle Snacks	
13	TXN10012	C1012	null	Male	P612	Apple Decor	
14	TXN10013	C1013	null	Male	P613	Arrow Snacks	
15							▶

100 rows

```
# Step 5: Filter out invalid quantity, negative values, excessive discounts
df_clean4 = df_clean3.filter(
    (col("Quantity") > 0) &
    (col("Amount") > 0) &
    (col("Discount") <= col("Amount")))
display(df_clean4)
```

☐ ☐ df\_clean4: pyspark.sql.connect.dataframe.DataFrame = [TransactionID: string, CustomerID: string ... 18 more fields]

	TransactionID	CustomerID	CustomerAge	Gender	ProductID	ProductName
1	TXN10000	C1000	null	Male	P600	Pepsi Decor
2	TXN10001	C1001	54	Female	P601	Nestle Beverages
3	TXN10002	C1002	null	Male	P602	Arrow Decor
4	TXN10003	C1003	null	Male	P603	Nestle Snacks
5	TXN10004	C1004	48	Male	P604	Sony Beverages
6	TXN10005	C1005	null	Female	P605	Nestle Snacks
7	TXN10006	C1006	59	Female	P606	Pepsi Furniture
8	TXN10007	C1007	58	Female	P607	Nestle Snacks
9	TXN10008	C1008	20	Female	P608	Levis Laptops
10	TXN10009	C1009	33	Female	P609	Nestle Shirts
11	TXN10010	C1010	null	Female	P610	Apple Snacks
12	TXN10011	C1011	20	Female	P611	Nestle Snacks
13	TXN10012	C1012	null	Male	P612	Apple Decor
14	TXN10013	C1013	null	Male	P613	Arrow Snacks
15						

100 rows

```
df_clean5 = df_clean4.dropDuplicates(["TransactionID"])
```

☐ ☐ df\_clean5: pyspark.sql.connect.dataframe.DataFrame = [TransactionID: string, CustomerID: string ... 18 more fields]

```
# DBTITLE 1,silver dataset
# Step 2: Drop critical nulls
df_clean1 = bronze_df.filter(
    (col("TransactionID").isNotNull()) &
    (col("CustomerID").isNotNull()) &
    (col("TransactionDate").isNotNull())
)
```

☐ ☐ df\_clean1: pyspark.sql.connect.dataframe.DataFrame = [TransactionID: string, CustomerID: string ... 18 more fields]

```
# DBTITLE 1,silver dataset
# Step 2: Drop critical nulls
df_clean1 = bronze_df.filter(
    (col("TransactionID").isNotNull()) &
    (col("CustomerID").isNotNull()) &
    (col("TransactionDate").isNotNull())
)
```

☐ ☐ df\_clean1: pyspark.sql.connect.dataframe.DataFrame = [TransactionID: string, CustomerID: string ... 18 more fields]

```
# Step 3: Trim and standardize text fields
df_clean2 = df_clean1.withColumn("PaymentType", upper(trim(col("PaymentType")))) \
    .withColumn("StoreRegion", upper(trim(col("StoreRegion")))) \
    .withColumn("DeviceUsed", upper(trim(col("DeviceUsed"))))
```

□ □ df\_clean2: pyspark.sql.connect.dataframe.DataFrame = [TransactionID: string, CustomerID: string ... 18 more fields]

```
# Step 4: Cast types
df_clean3 = df_clean2.withColumn("TransactionDate", col("TransactionDate").cast("timestamp")) \
    .withColumn("Quantity", col("Quantity").cast("int")) \
    .withColumn("Amount", col("Amount").cast("float")) \
    .withColumn("Discount", col("Discount").cast("float"))
```

□ □ df\_clean3: pyspark.sql.connect.dataframe.DataFrame = [TransactionID: string, CustomerID: string ... 18 more fields]

```
# Step 5: Filter out invalid quantity, negative values, excessive discounts
df_clean4 = df_clean3.filter(
    (col("Quantity") > 0) &
    (col("Amount") > 0) &
    (col("Discount") <= col("Amount"))
)
```

□ □ df\_clean4: pyspark.sql.connect.dataframe.DataFrame = [TransactionID: string, CustomerID: string ... 18 more fields]

```
# Step 6: Drop duplicates
df_clean5 = df_clean4.dropDuplicates(["TransactionID"])
```

□ □ df\_clean5: pyspark.sql.connect.dataframe.DataFrame = [TransactionID: string, CustomerID: string ... 18 more fields]

```
# Step 7: Write to Silver
df_clean5.write.format("parquet").mode("overwrite").save("/mnt/storagename/silver")
```

```
silver_df=spark.read.parquet('/mnt/storagename/silver/')
display(silver_df)
```

□ □ silver\_df: pyspark.sql.connect.dataframe.DataFrame = [TransactionID: string, CustomerID: string ... 18 more fields]


Table

```
# DBTITLE 1,gold dataset
silver_df.createOrReplaceTempView('retail_data')
```


```
%sql
select * from retail_data
```

↳ ↳ \_sqldf: pyspark.sql.connect.dataframe.DataFrame = [TransactionID: string, CustomerID: string ... 18 more fields]

**Table**

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


```
# DBTITLE 1,daily revenue by purchase
%sql
select date(TransactionDate),sum(amount) total_revenue,count(distinct TransactionID) total_purchase from
retail_data
group by 1
```

 > SyntaxError: invalid syntax (command-6153654693092673-521328151, line 3)  
[Trace ID: 00-9a241ec474f562b1b5adc522039d04e3-e454ab60c0e78515-00]


```
%sql
SELECT
    DATE(TransactionDate) AS transaction_date,
    SUM(amount) AS total_revenue,
    COUNT(DISTINCT TransactionID) AS total_purchases
FROM
    retail_data
GROUP BY
    DATE(TransactionDate);
```

□ □ `_sqldf`: pyspark.sql.connect.dataframe.DataFrame = [transaction\_date: date, total\_revenue: double ... 1 more field]

Table

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


```
# DBTITLE 1,REVENUE BY PAYMENT TYPE
%sql
select sum(amount) total_revenue, PAYMENTTYPE from retail_data
group by 2
```

 > IndentationError: unexpected indent (command-6153654693092675-4029064299, line 2)  
[Trace ID: 00-5f53a740d267cb0aa2d0acebdd3b82b4-94a1e1b80d2051a3-00]


```
%sql
select sum(amount) total_revenue, PAYMENTTYPE from retail_data
group by PAYMENTTYPE
```

□ □ `_sqldf`: pyspark.sql.connect.dataframe.DataFrame = [total\_revenue: double, PAYMENTTYPE: string]

Table

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


```
# DBTITLE 1,STORE PERFORMANCE
%sql
select sum(amount) as total_revenue, STORELOCATION from retail_data
group by STORELOCATION
```

 > SyntaxError: invalid syntax (command-6153654693092678-2663134886, line 3)  
[Trace ID: 00-898ec182064b64cefd40b06c2b2b0425-840e0298e07ac5c8-00]

```
%sql
SELECT
  StoreLocation AS store_location,
  SUM(amount) AS total_revenue
FROM
  retail_data
GROUP BY
  StoreLocation;
```

☐ `_sqldf`: `pyspark.sql.connect.dataframe.DataFrame = [store_location: string, total_revenue: double]`

Table

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




```
# DBTITLE 1,LOYALTY LEVEL REVENUE CONTRIBUTION
# MAGIC %sql
# MAGIC select sum(amount) total_revenue, CustomerLoyaltyLevel
# MAGIC from retail_data
# MAGIC group by 2

# COMMAND -----

# DBTITLE 1,PRODUCT CATEGORY SALES
# MAGIC %sql
# MAGIC select sum(amount) total_revenue, ProductCategory
# MAGIC from retail_data
# MAGIC group by 2
```


```
# DBTITLE 1,LOYALTY LEVEL REVENUE CONTRIBUTION
SELECT  CustomerLoyaltyLevel, SUM(amount) AS total_revenue
FROM    retail_data
GROUP BY CustomerLoyaltyLevel;
```

 > IndentationError: unexpected indent (command-6153654693092681-1704461844, line 3)  
[Trace ID: 00-4fd7ae13d1cbac3703599a174c2e0b8c-26e706ea27f525f0-00]


```
%sql
SELECT
    SUM(amount) AS total_revenue,
    CustomerLoyaltyLevel
FROM retail_data
GROUP BY CustomerLoyaltyLevel
ORDER BY total_revenue DESC
```

☐ ☐ \_sqlidf: pyspark.sql.connect.dataframe.DataFrame = [total\_revenue: double, CustomerLoyaltyLevel: string]

Table


 This result is stored as \_sqlidf and can be used in other Python and SQL cells.

```
# DBTITLE 1,PRODUCT CATEGORY SALES
%sql
select sum(amount) total_revenue, ProductCategory
from retail_data
group by 2
```

 > IndentationError: unindent does not match any outer indentation level (<string>, line 5)

□ □ \_sqldf: pyspark.sql.connect.dataframe.DataFrame = [product\_category: string, total\_revenue: double]

**Table**

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