



# Broadcast Join VS Sort-Merge Join

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## Day 5 — Spark Optimization Topic

### 5. Broadcast Join vs Sort-Merge Join

Understanding this difference is **mandatory** for PySpark performance optimization.

#### 1. Broadcast Join

Spark **copies the smaller DataFrame** to every executor and performs a join **locally**, avoiding shuffle.

##### ✓ How it works

- Small table (usually < 100–500 MB) is **broadcasted**
- Each executor gets a **local copy**
- Large table is scanned once
- Join is done **map-side** (no shuffle of big table)

##### ✓ Advantages

- Zero shuffle for the big table
- Very fast for small-to-big joins
- Ideal for dimension tables or lookups

### ✓ When to use

- Dimension table < threshold (default 10 MB, configurable)
- Star-schema joins
- Lookup tables (country codes, categories, products)
- When joining a large fact table with a small reference table

### ✓ Example

```
from pyspark.sql.functions import broadcast

result = large_df.join(broadcast(small_df),
"customer_id")
```

## 2. Sort-Merge Join

The default join in Spark when both tables are **large** or when no broadcast is used.

### ✓ How it works

- Both DataFrames are **shuffled** on join key
- Each side is **sorted**
- Merge happens on sorted partitions

### ✓ Advantages

- Great for large-to-large joins

- Stable and scalable
- Works reliably at massive scale

### ✓ **Disadvantages**

- Shuffle + sort = expensive
- Needs large memory
- Can lead to skew

### ✓ **Example**

```
result = large_df.join(another_large_df, "txn_id")
```

## **Broadcast Join vs Sort-Merge Join — Side-by-Side**

Feature	Broadcast Join	Sort-Merge Join
Shuffle	No (for small table)	Yes (both tables)
Best for	Small-to-big joins	Big-to-big joins
Speed	Very fast	Medium/Slow (depending on size)
Memory usage	More (stores copy on each executor)	Moderate
Requires sorting	No	Yes

Skew handling	Limited	More advanced mechanisms
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## Spark Choosing Strategy

Spark automatically decides join strategy based on:

### 1. Size of smaller DataFrame

If `spark.sql.autoBroadcastJoinThreshold`

(default 10 MB):

→ **Broadcast Join**

### 2. If `broadcast()` keyword is manually used

→ **Forced Broadcast Join**

### 3. If both sides are large

→ **Sort-Merge Join**

## Real Example: Indian E-commerce Dataset

`customers_small` (50,000 rows)

`transactions` (400 million rows)

Goal: Join both by `customer_id`

### **Best Approach:**

```
df = transactions.join(broadcast(customers_small),  
"customer_id")
```

Reason: customers\_small fits into memory → avoids shuffle of 400M rows.

## **When Broadcast Join is Bad**

Do **NOT** use broadcast when:

### **X The small table is actually large**

Broadcasting a 1–2 GB table can crash executors.

### **X High concurrency**

Multiple queries broadcasting big tables can cause memory pressure.

### **X Running on small cluster**

Executors may not have memory for several broadcast copies.

## **When Sort-Merge Join is Better**

✓ Both tables are large

- ✓ You need a stable join with sorting
- ✓ After applying salting or skew-handling techniques
- ✓ When broadcast threshold is exceeded



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