

# Wide vs Narrow Dependencies

Big Data Analysis with Scala and Spark

Heather Miller

# Not All Transformations are Created Equal

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In the past sessions:

- ▶ we learned that shuffling sometimes happens on some transformations.

In this session:

- ▶ we'll look at how RDDs are represented.
- ▶ we'll dive into how and when Spark decides it must shuffle data.
- ▶ we'll see how these dependencies make fault tolerance possible.

# Lineages

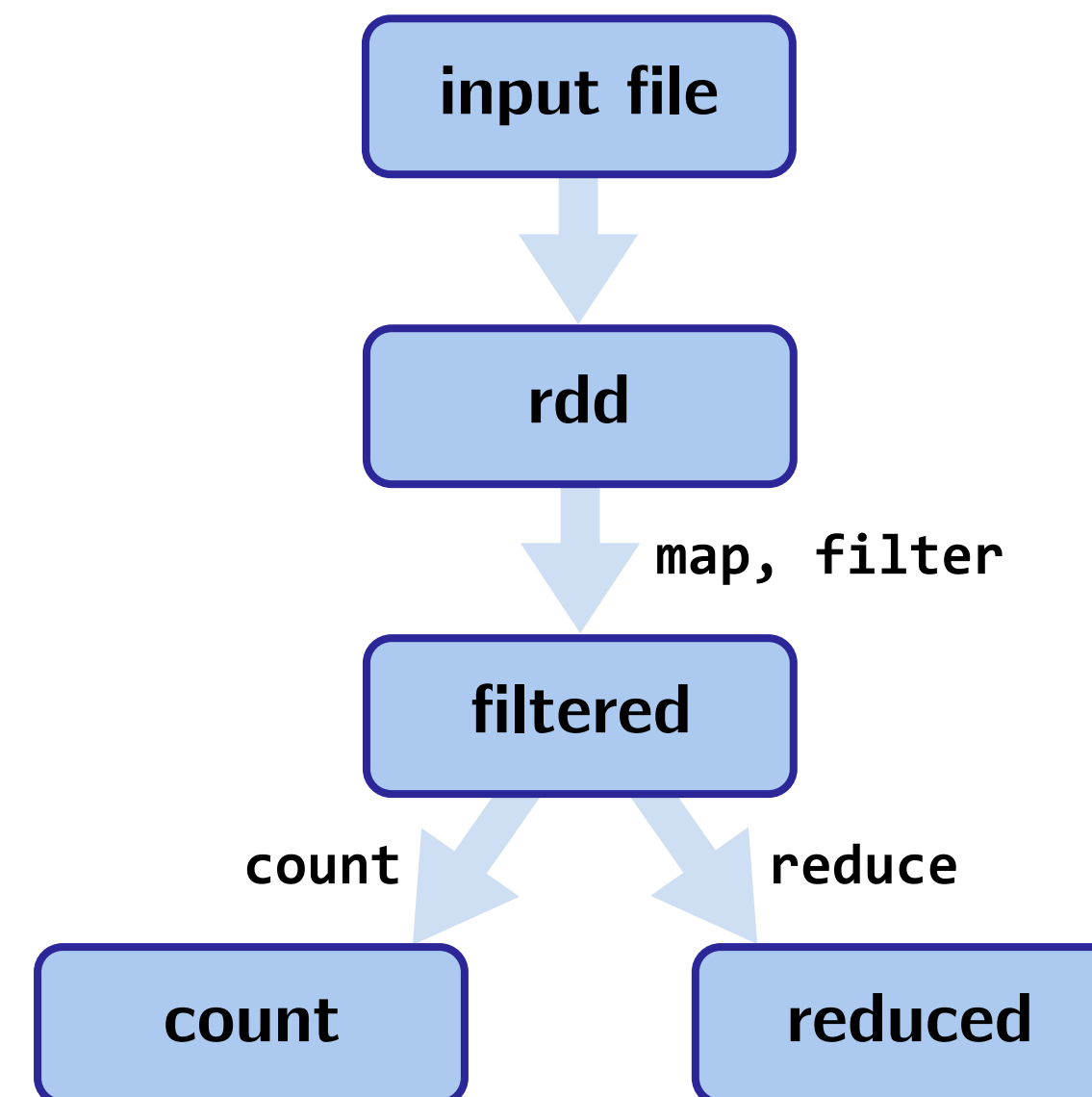
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                  .filter(...)
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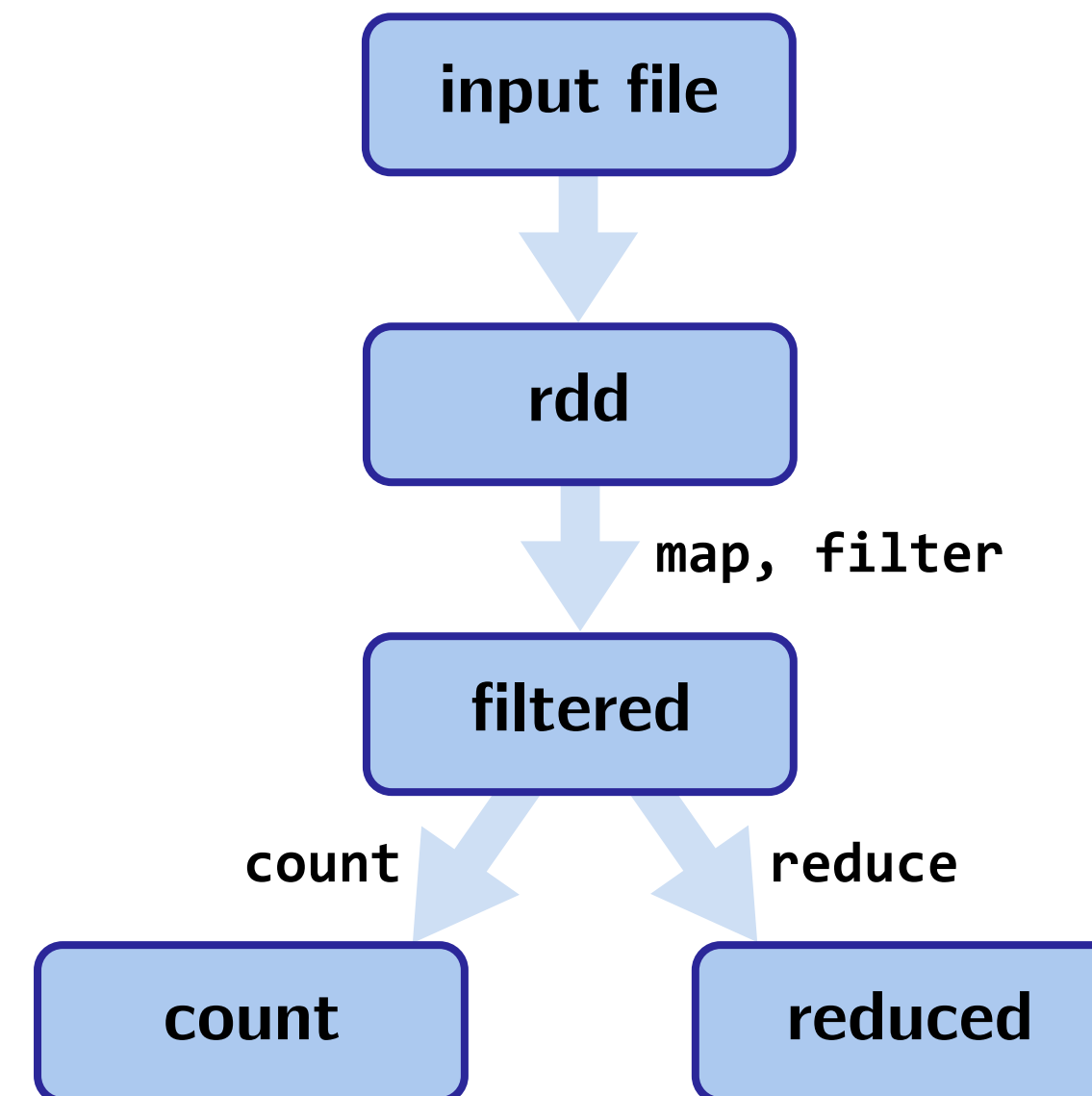


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**Spark represents RDDs in terms of these lineage graphs/DAGs**

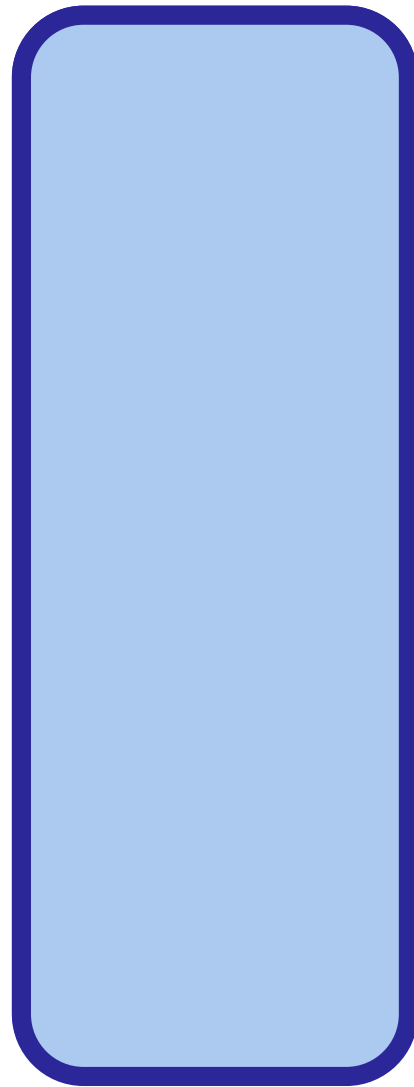
*In fact, this is the representation/DAG is what Spark analyzes to do optimizations.*

# How are RDDs represented?

RDDs are made up of 2 important parts.

*(but are made up of 4 parts in total)*

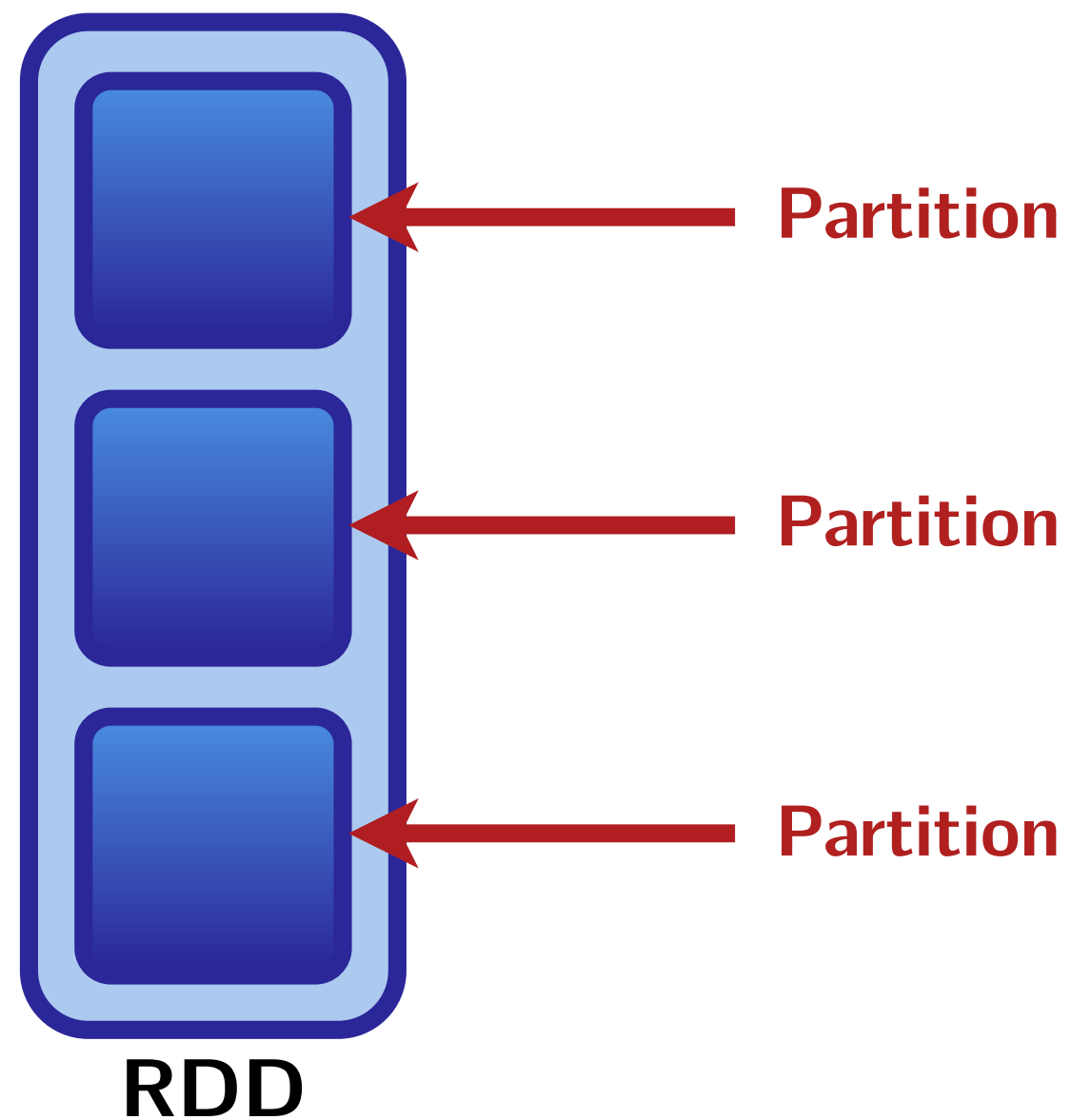
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**RDD**

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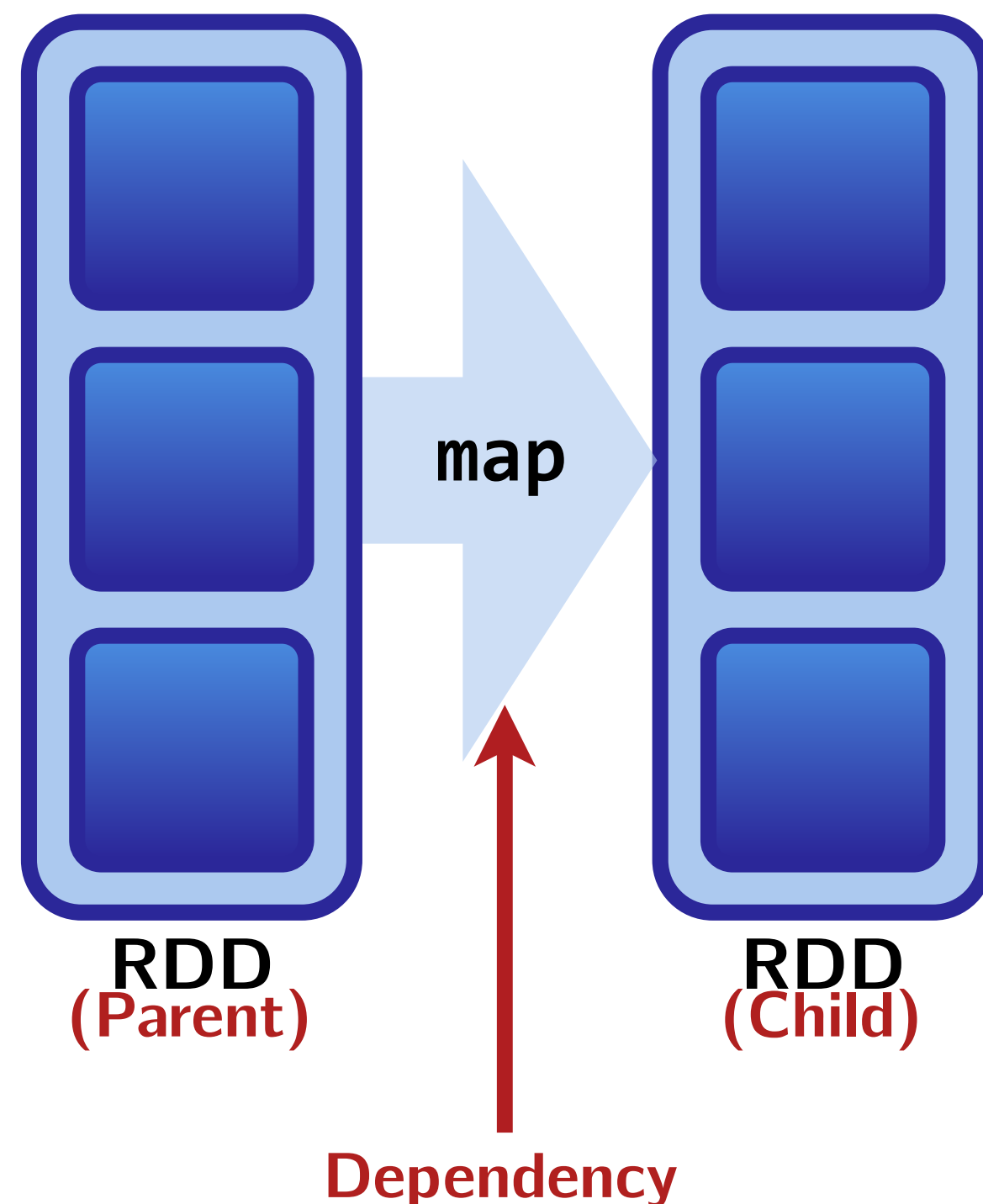
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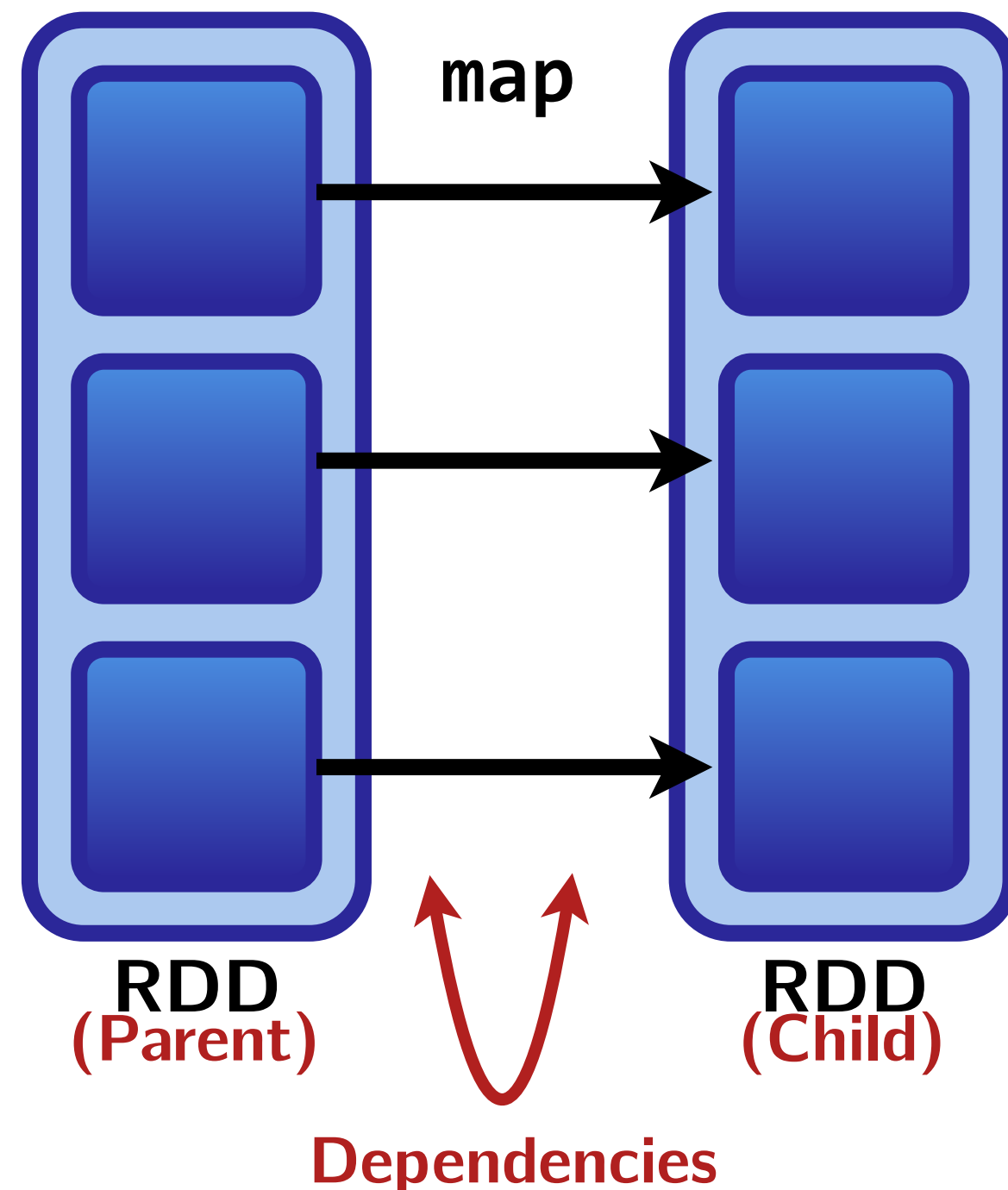


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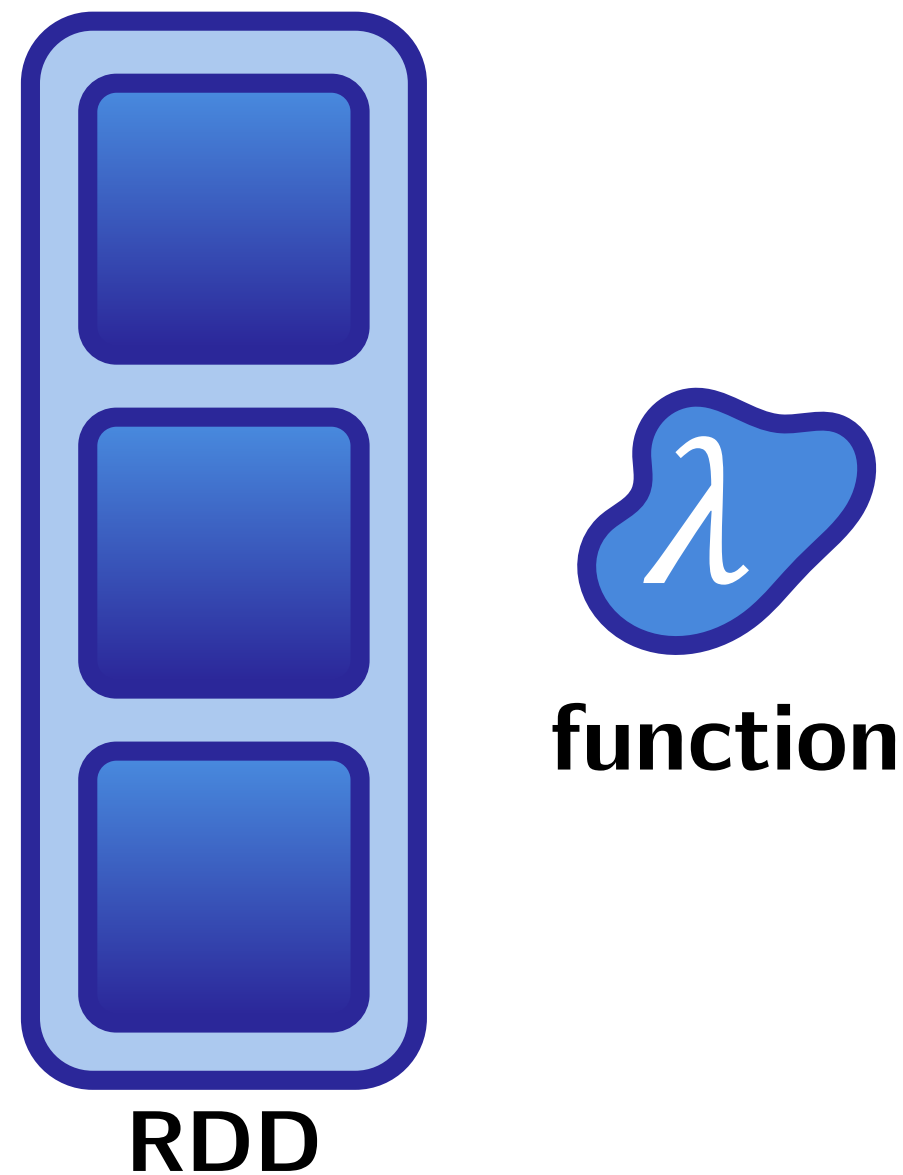


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- ▶ **Partitions.** Atomic pieces of the dataset. One or many per compute node.
- ▶ **Dependencies.** Models relationship between this RDD and its partitions with the RDD(s) it was derived from.
- ▶ **A function** for computing the dataset based on its parent RDDs.
- ▶ **Metadata** about its partitioning scheme and data placement.

# RDD Dependencies and Shuffles

Previously, we arrived at the following rule of thumb for trying to determine when a shuffle might occur:

**Rule of thumb:** a shuffle *can* occur when the resulting RDD depends on other elements from the same RDD or another RDD.

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**In fact, RDD dependencies encode when data must move across the network.**

**Transformations cause shuffles.** Transformations can have two kinds of dependencies:

1. **Narrow Dependencies**
2. **Wide Dependencies**

# Narrow Dependencies vs Wide Dependencies

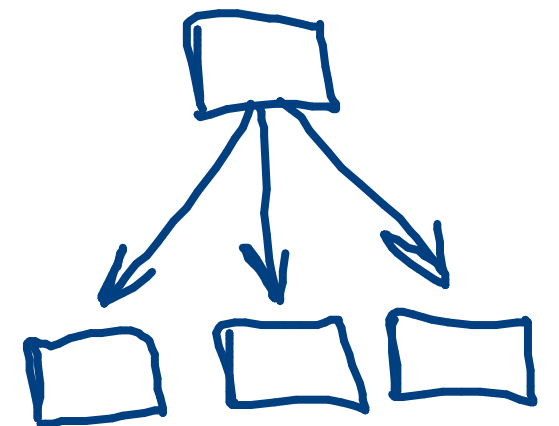
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## Wide Dependencies

Each partition of the parent RDD may be depended on by **multiple** child partitions.



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Each partition of the parent RDD is used by at most one partition of the child RDD.

**Fast! No shuffle necessary. Optimizations like pipelining possible.**

## Wide Dependencies

Each partition of the parent RDD may be depended on by **multiple** child partitions.

**Slow! Requires all or some data to be shuffled over the network.**



# Narrow Dependencies vs Wide Dependencies, Visually

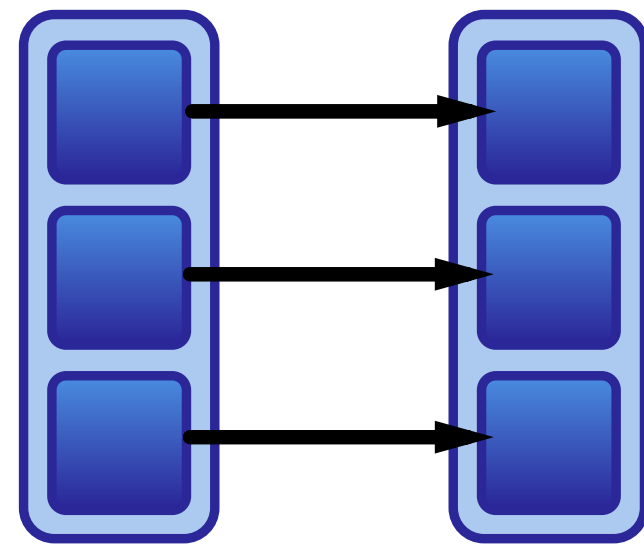
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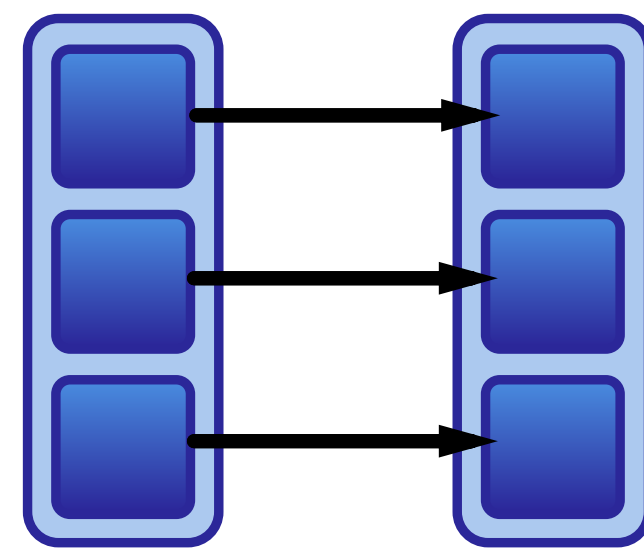


**map, filter**

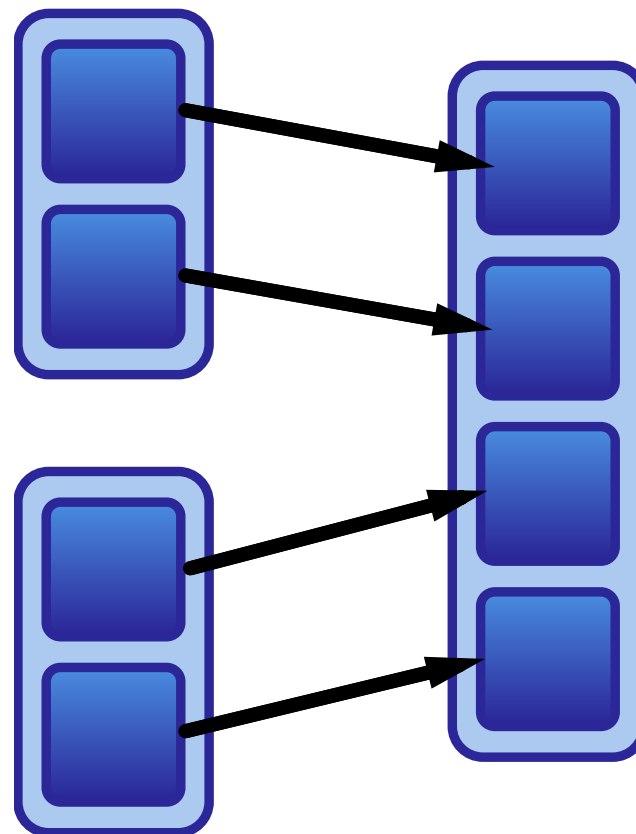
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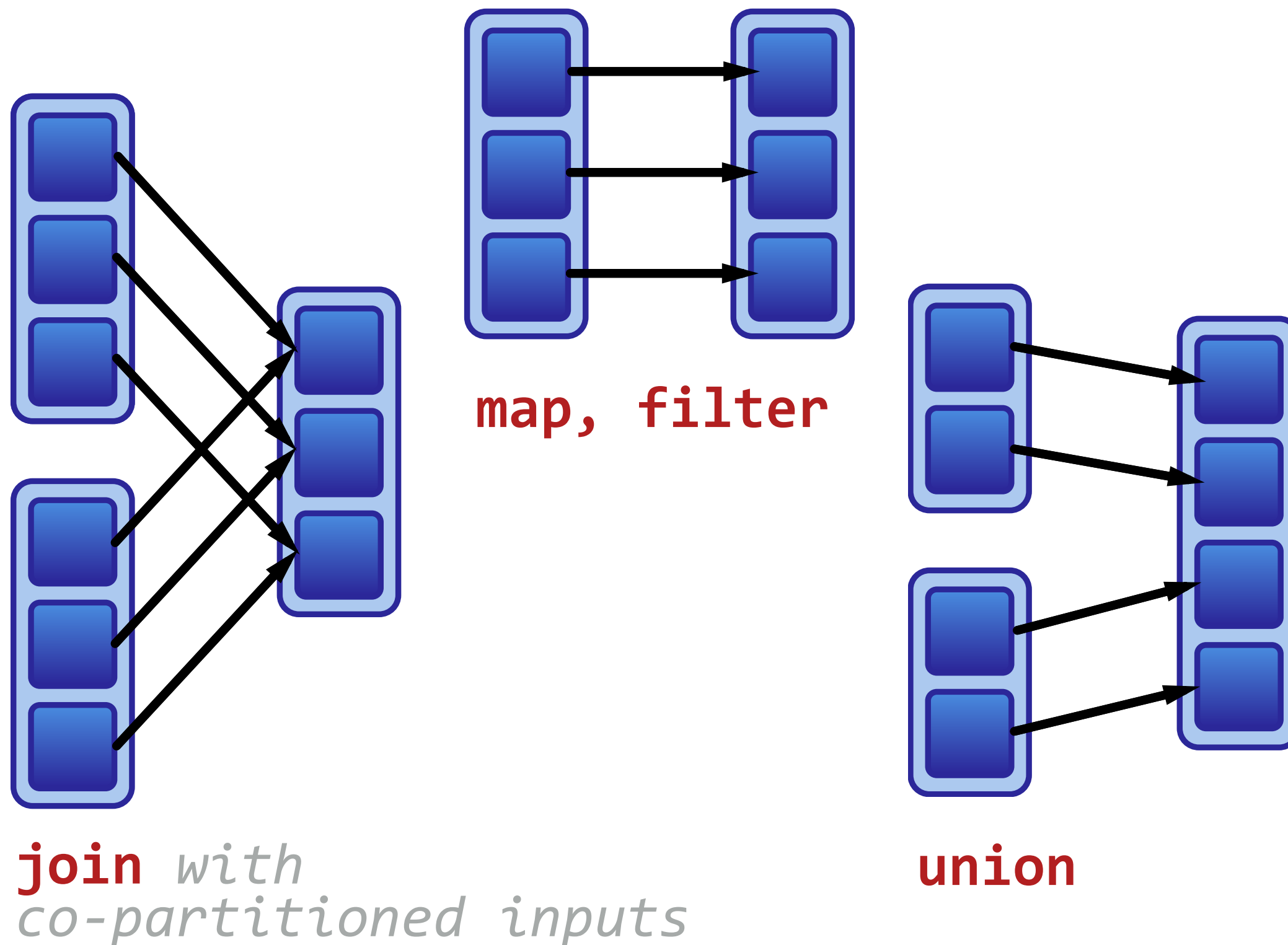


union

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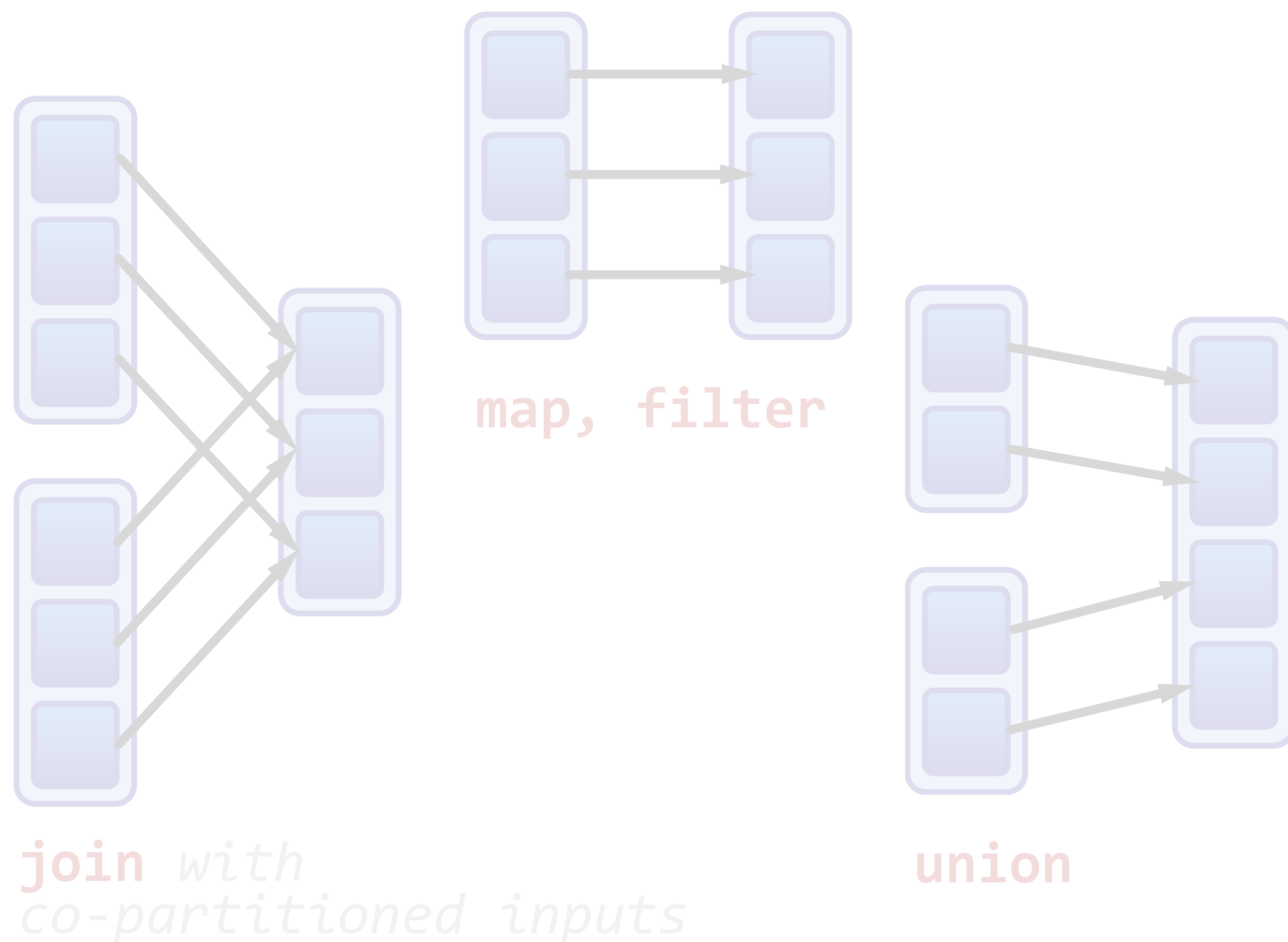
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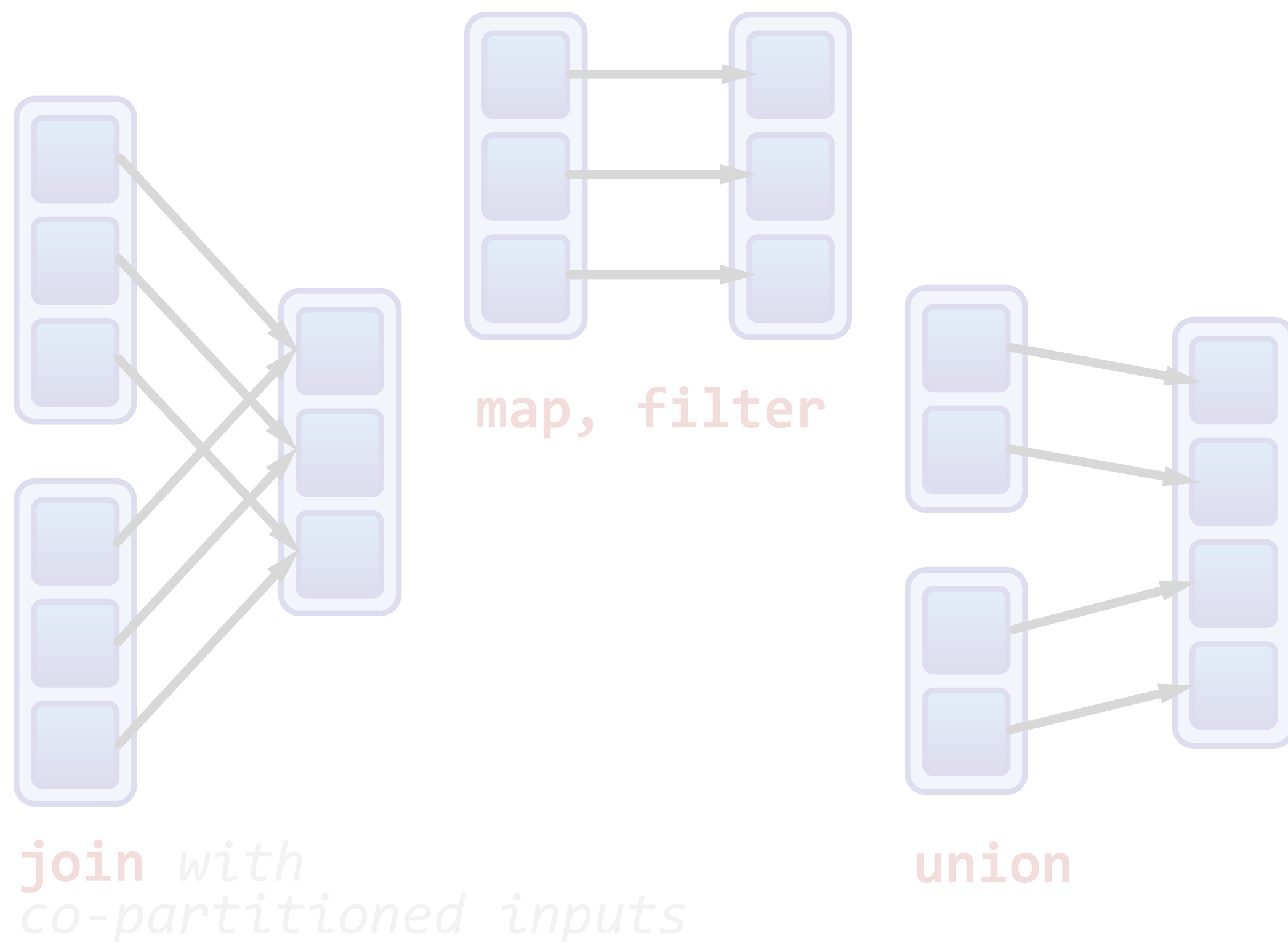
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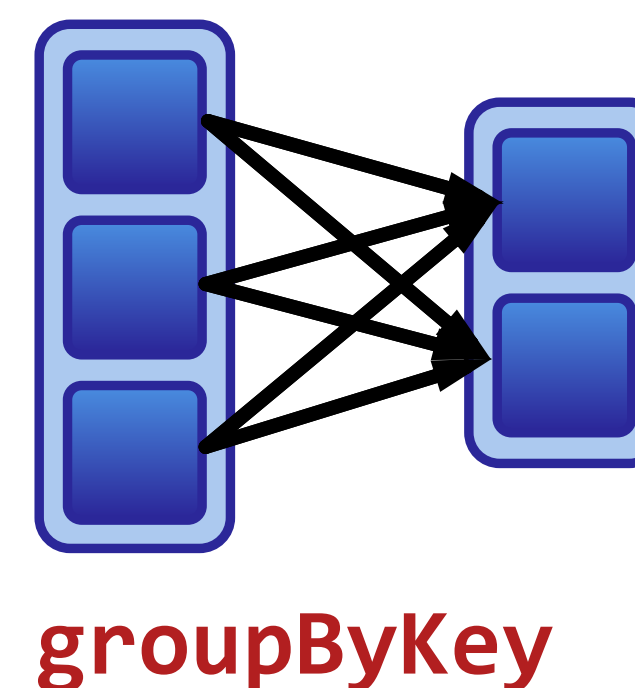
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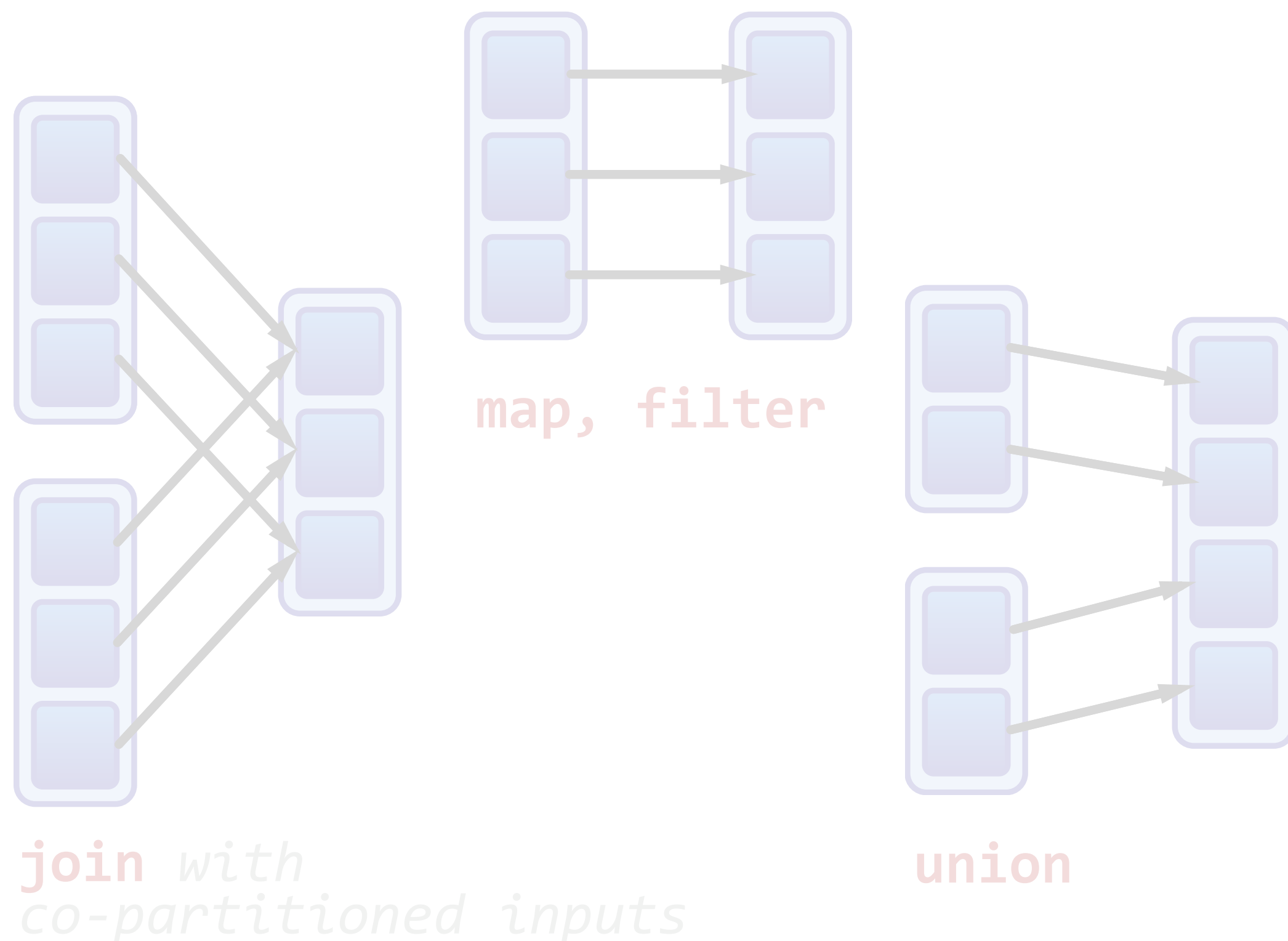
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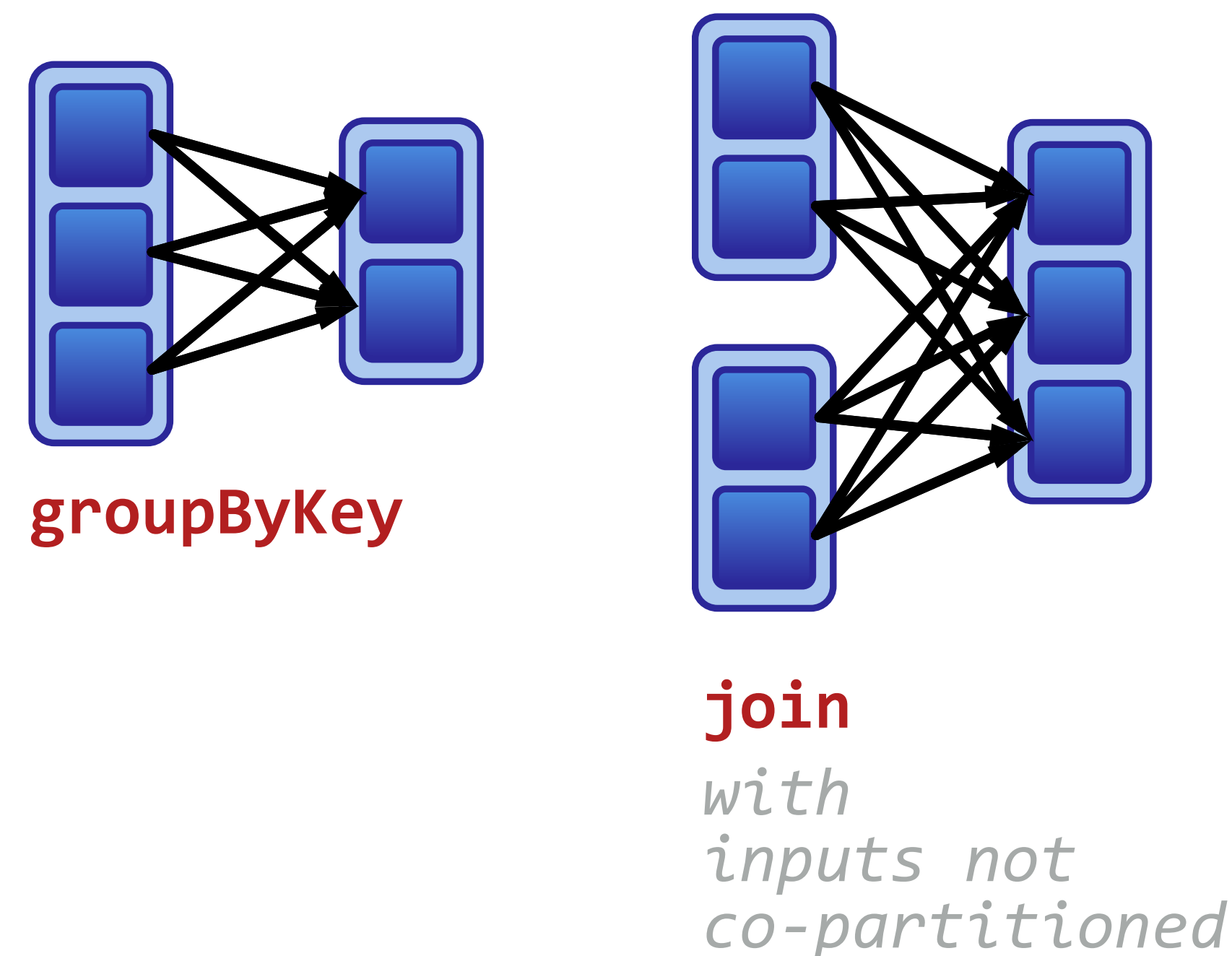
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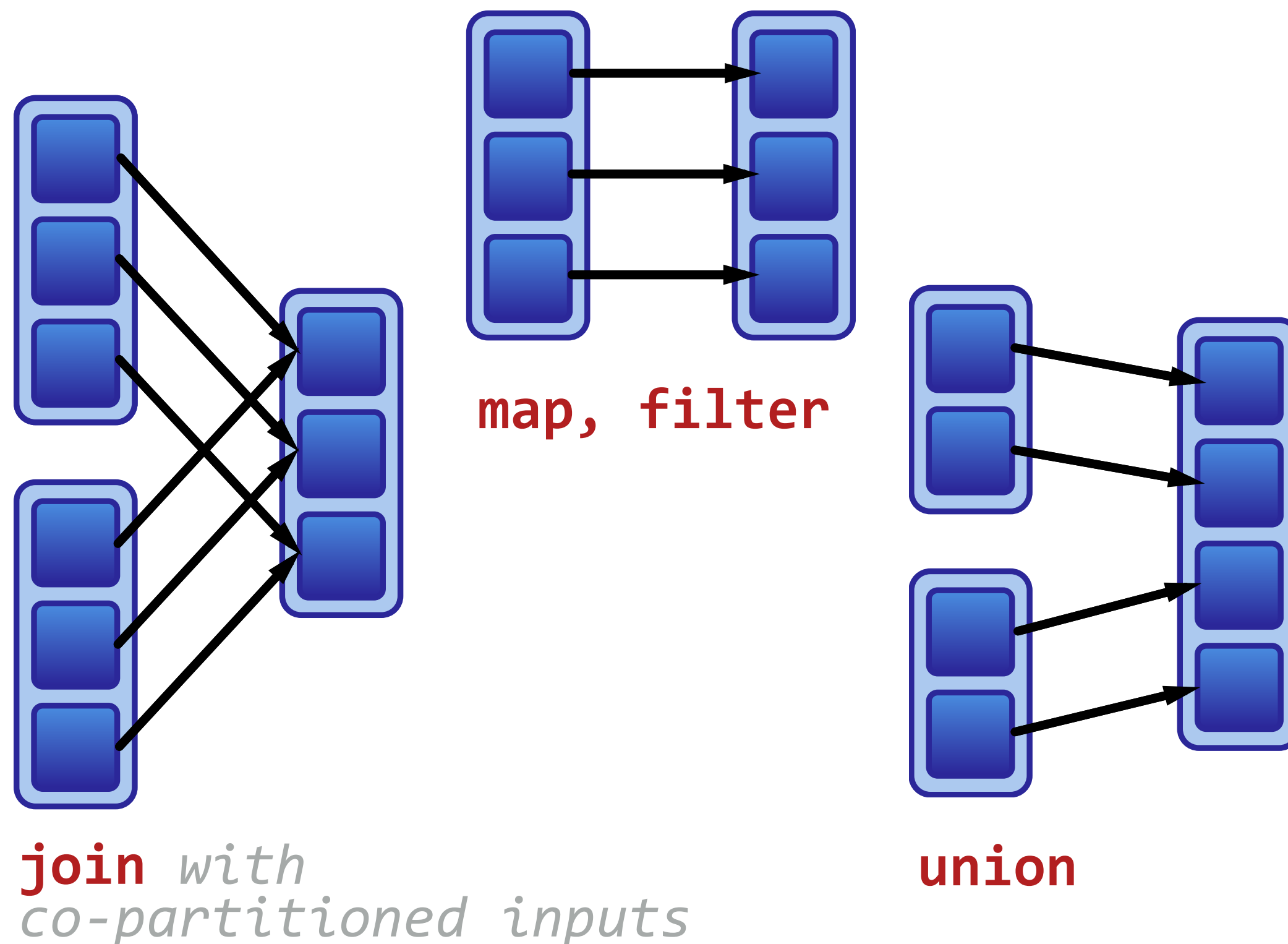
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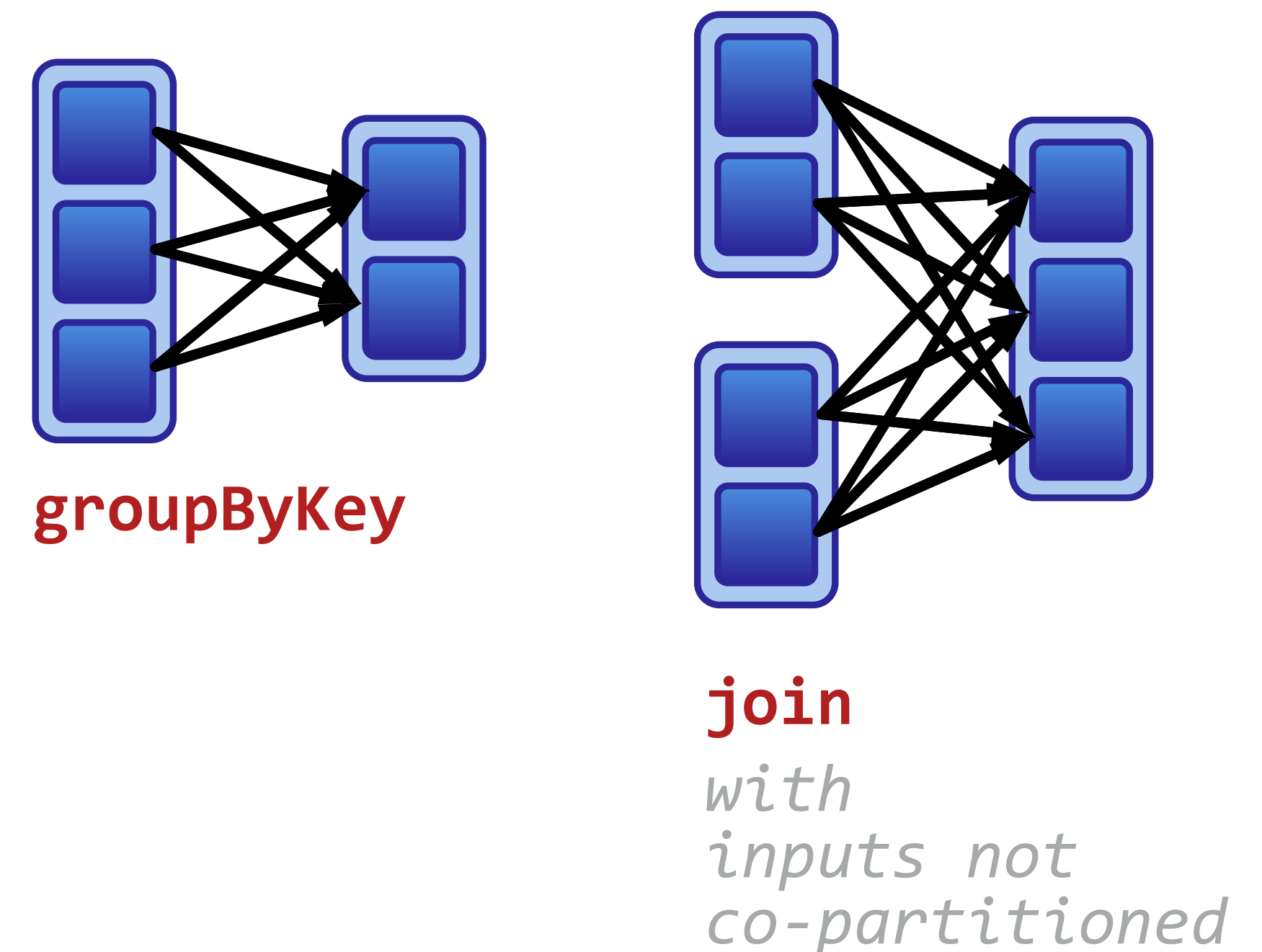
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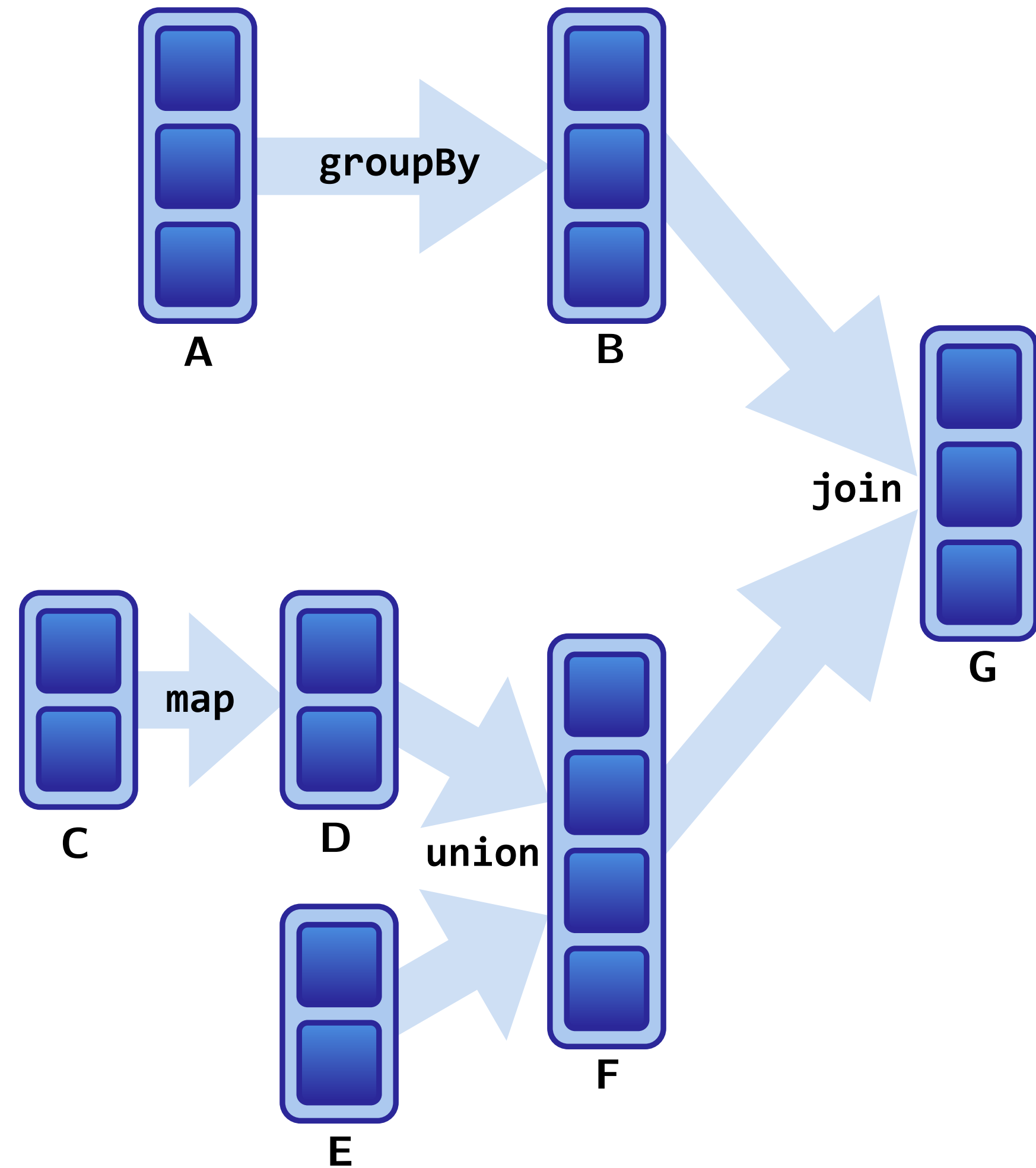
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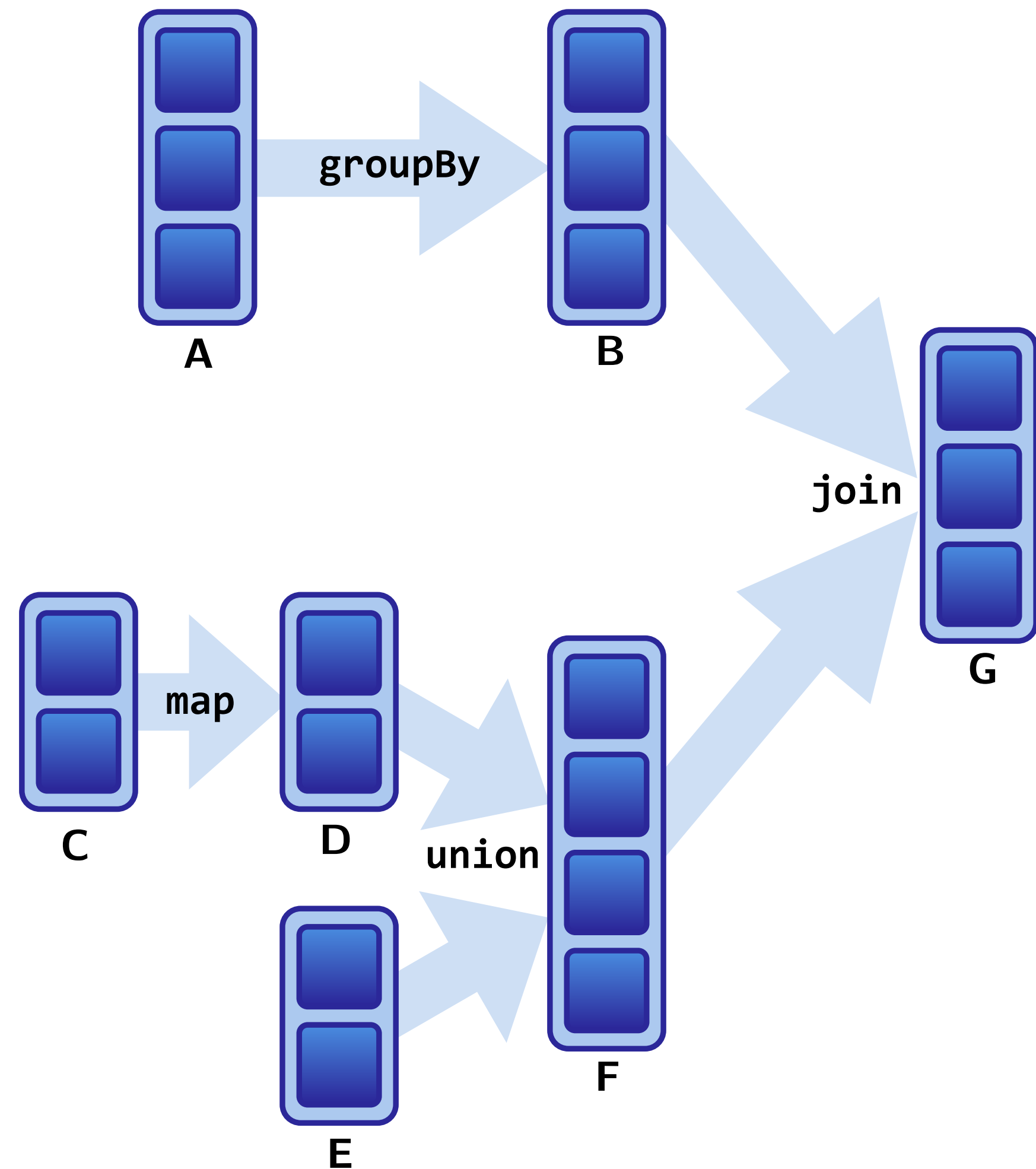
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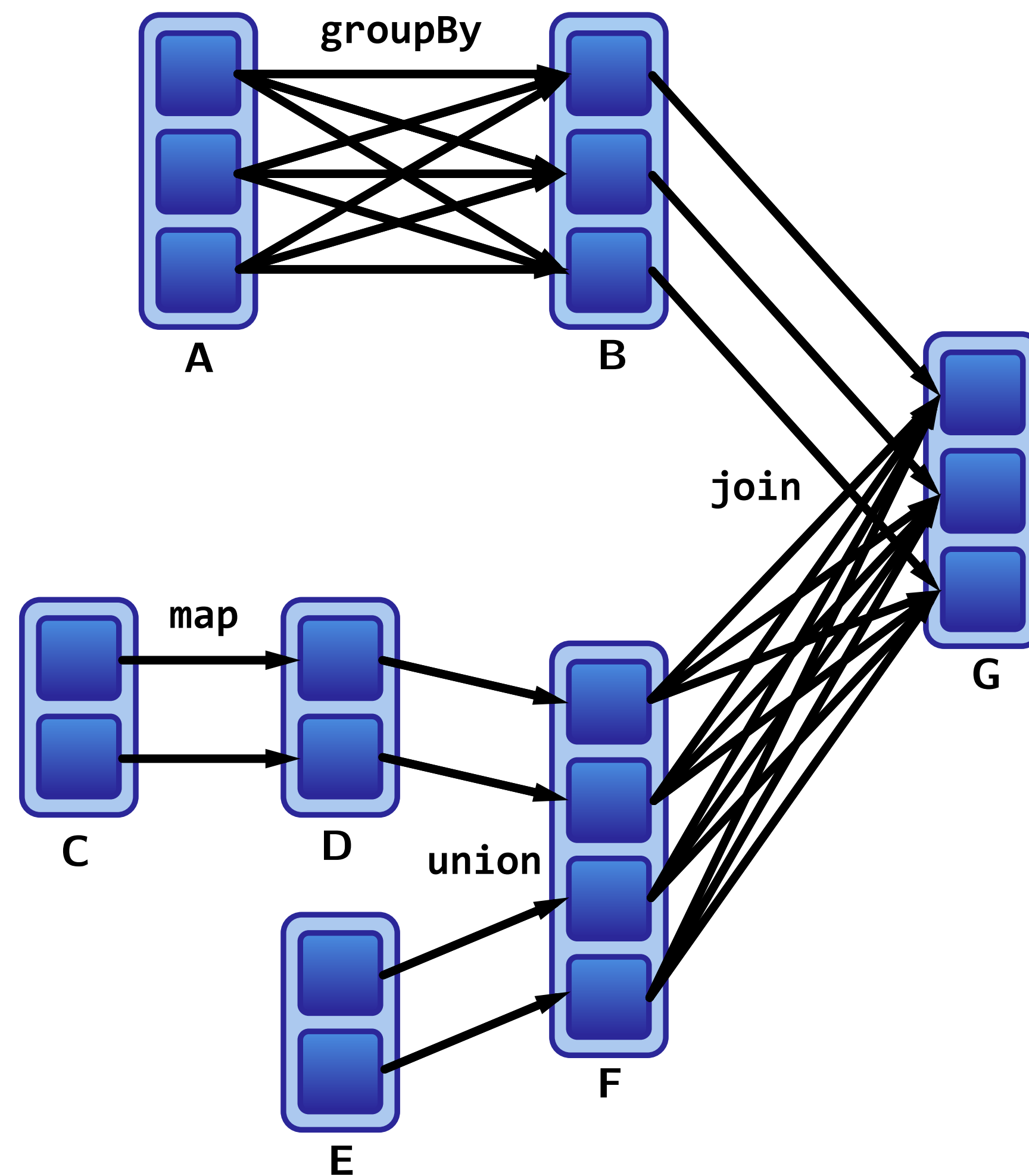


What do the dependencies look like?

Which dependencies are wide, and which are narrow?

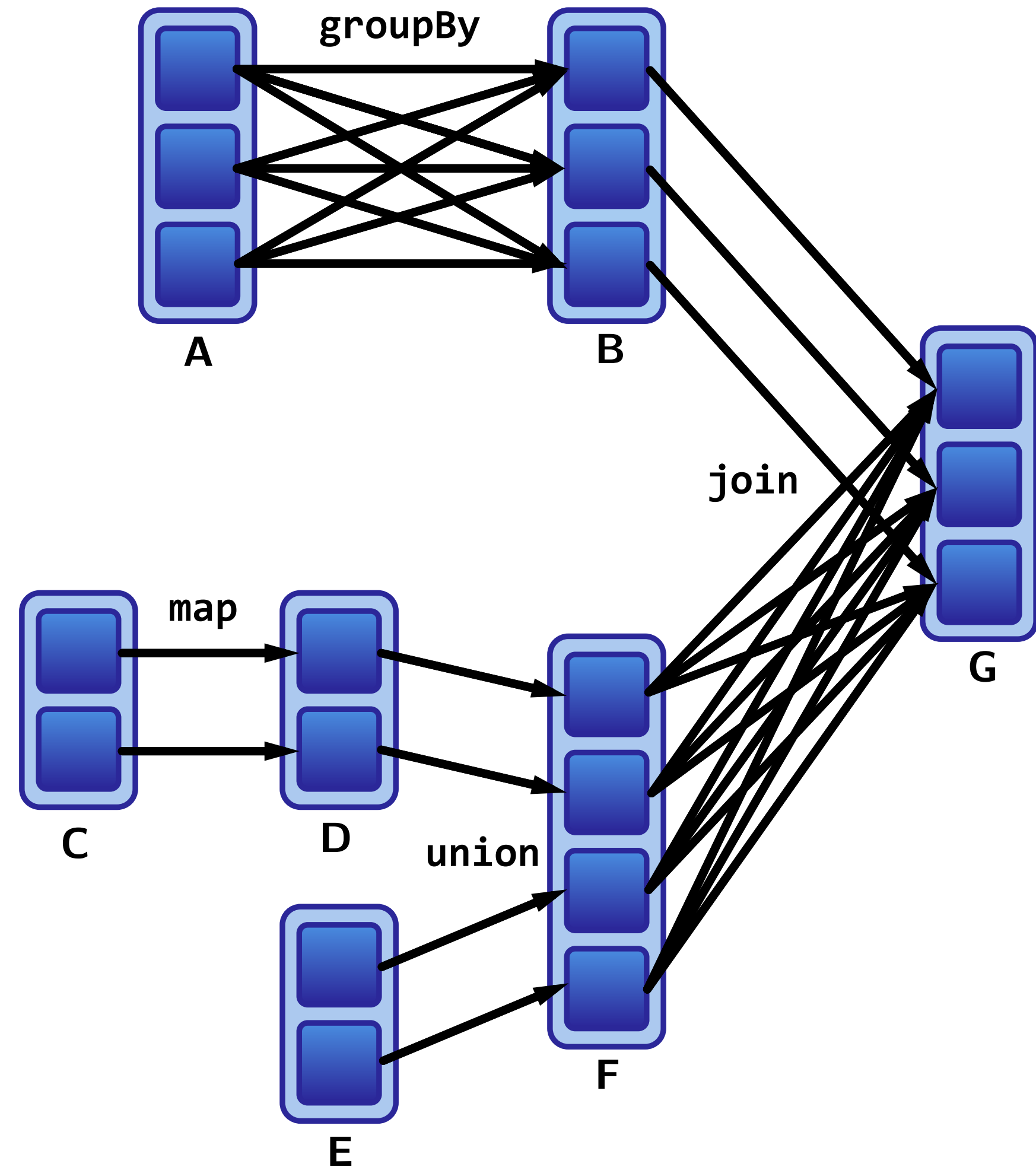
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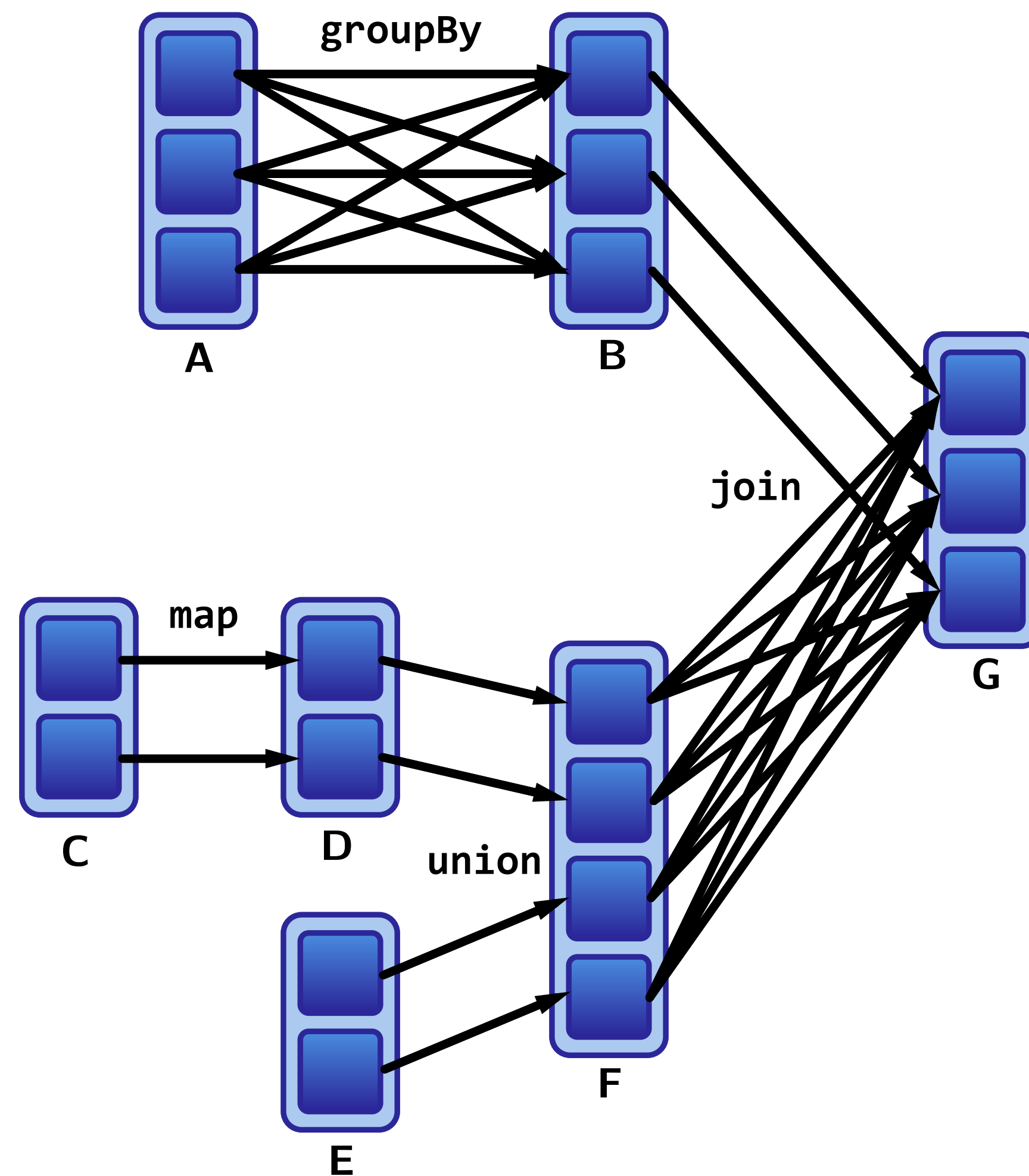
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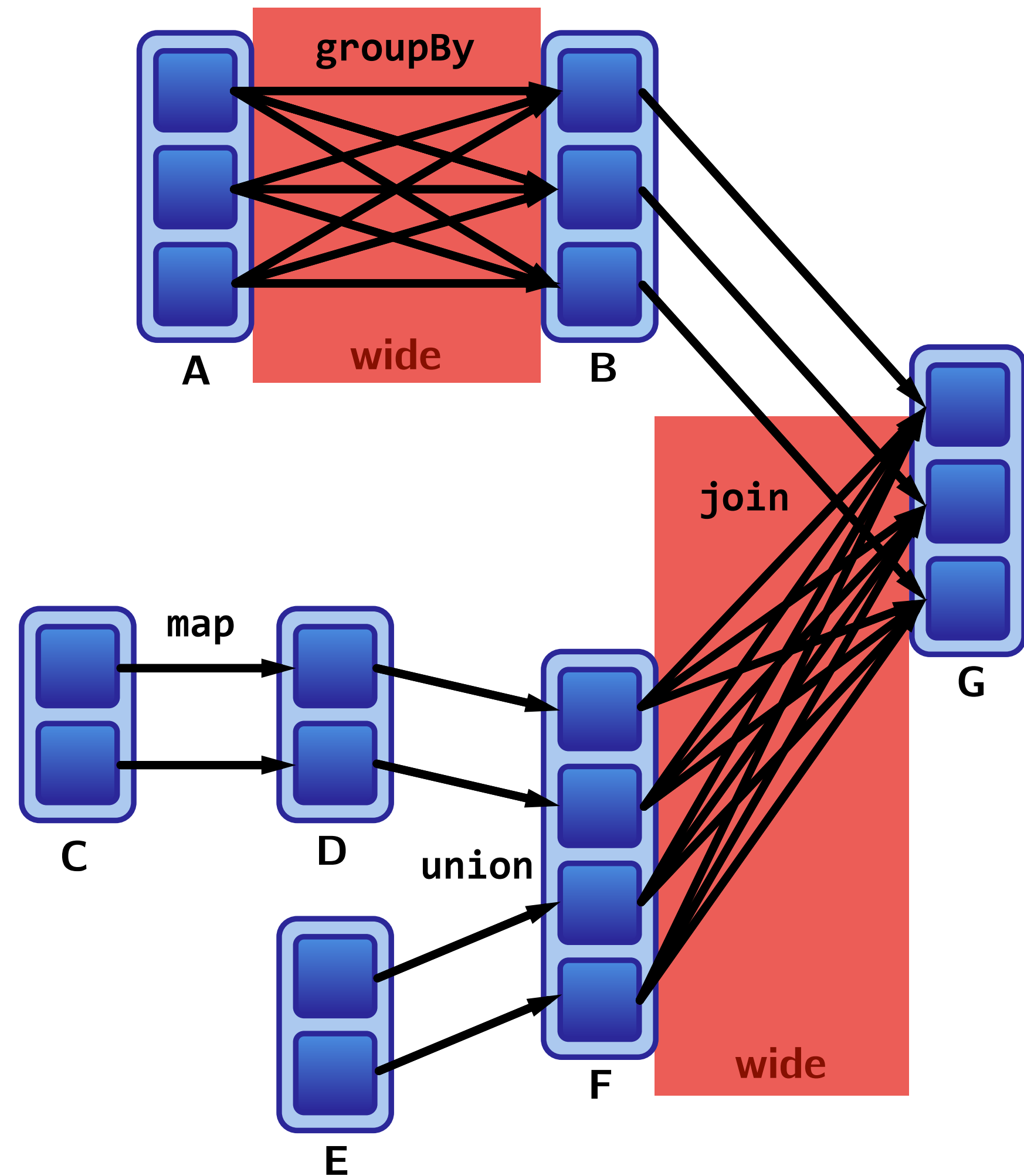
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**Wide transformations:**  
groupBy, join

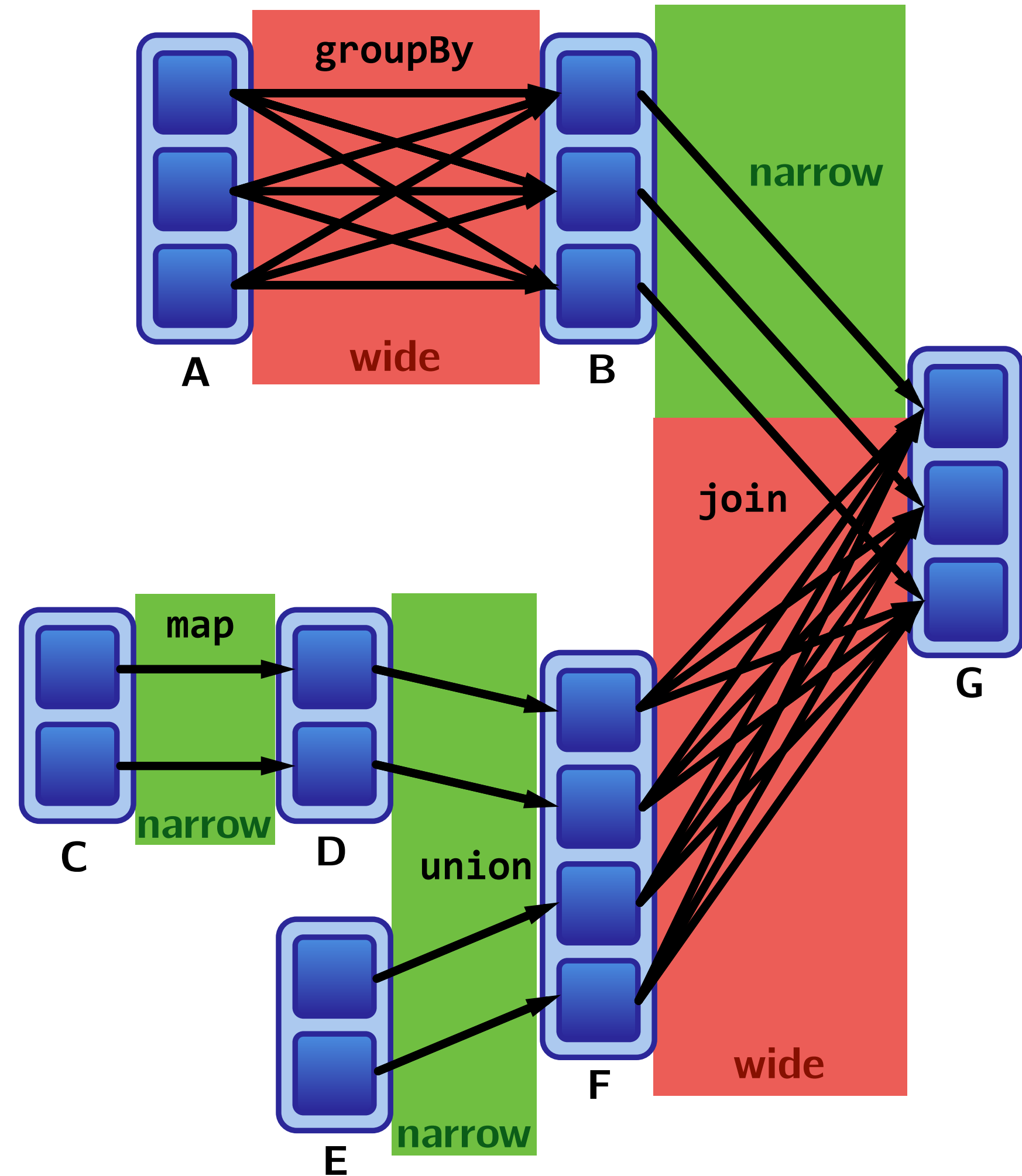


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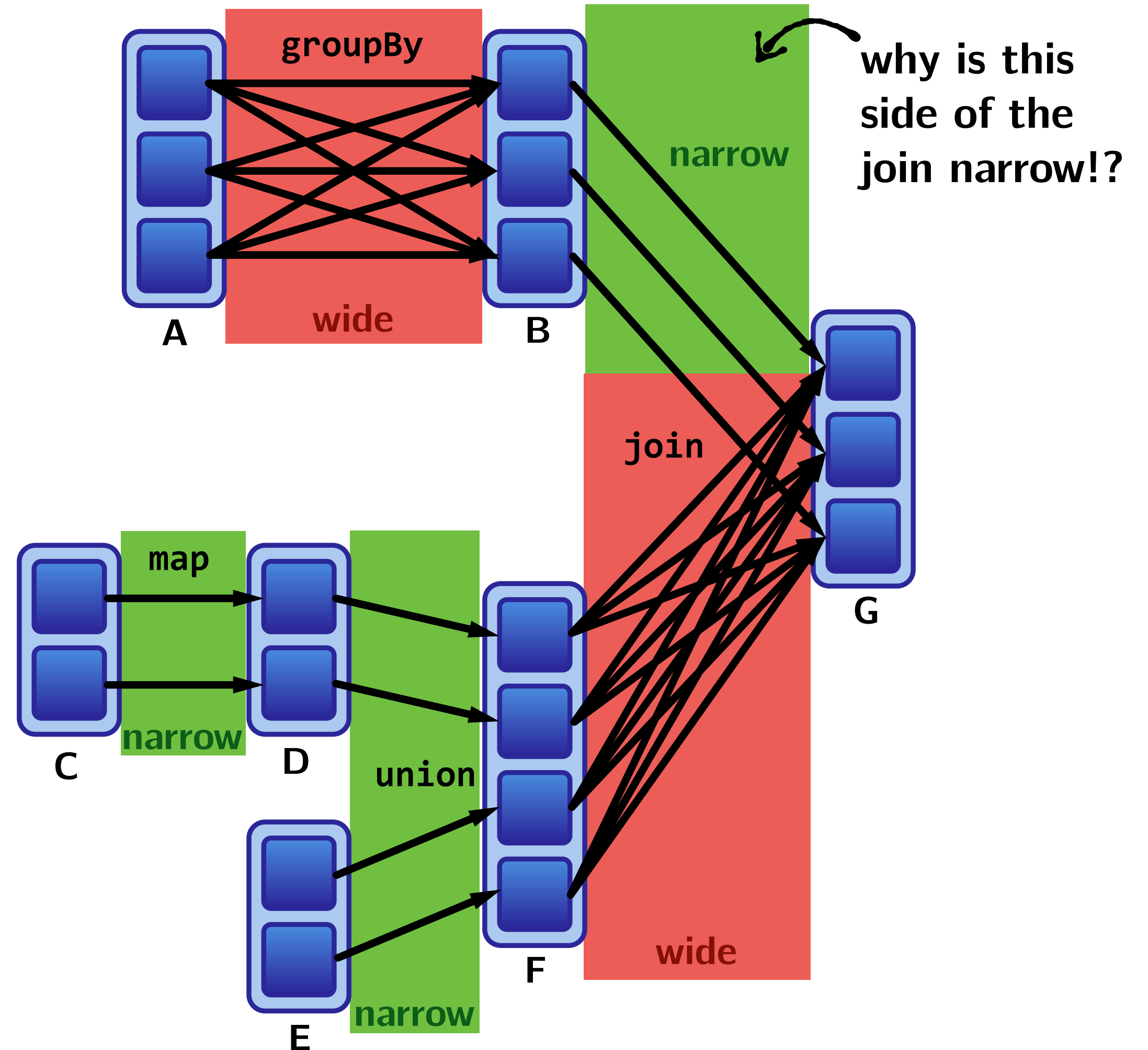


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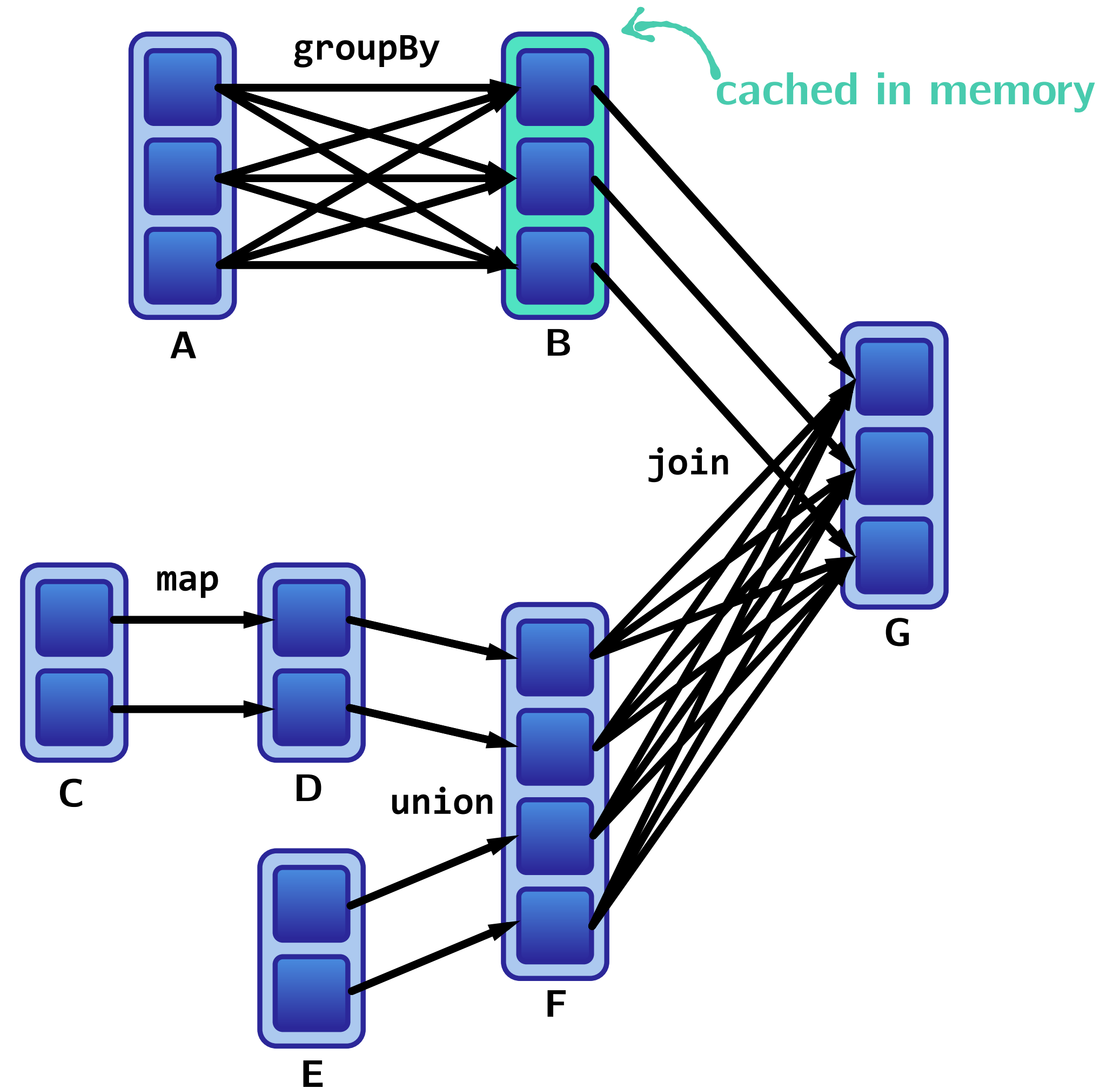


# Narrow Dependencies vs Wide Dependencies, Visually

Let's visualize an example program and its dependencies.

Since **G** would be derived from **B**, which itself is derived from a **groupBy** and a shuffle on **A**, you could imagine that we will have already co-partitioned and cached **B** in memory following the call to **groupBy**.

**Part of this join is thus a narrow transformation.**



# Which transformations have which kind of dependency?

## Transformations with narrow dependencies:

map

mapValues

flatMap

filter

mapPartitions

mapPartitionsWithIndex

## Transformations with wide dependencies:

*(might cause a shuffle)*

cogroup

groupWith

join

leftOuterJoin

rightOuterJoin

groupByKey

reduceByKey

combineByKey

distinct

intersection

repartition

coalesce

# How can I find out?

`dependencies` method on RDDs.

`dependencies` returns a sequence of Dependency objects, which are actually the dependencies used by Spark's scheduler to know how this RDD depends on other RDDs.

The sorts of dependency objects the `dependencies` method may return include:

## **Narrow dependency objects:**

- ▶ `OneToOneDependency`
- ▶ `PruneDependency`
- ▶ `RangeDependency`

## **Wide dependency objects:**

- ▶ `ShuffleDependency`

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```
val wordsRdd = sc.parallelize(largeList)
val pairs = wordsRdd.map(c => (c, 1))
                    .groupByKey()
                    .dependencies

// pairs: Seq[org.apache.spark.Dependency[_]] =
// List(org.apache.spark.ShuffleDependency@4294a23d)
```

# How can I find out?

**toDebugString** method on RDDs.

`toDebugString` prints out a visualization of the RDD's lineage, and other information pertinent to scheduling. For example, indentations in the output separate groups of narrow transformations that may be pipelined together with wide transformations that require shuffles. These groupings are called *stages*.

```
val wordsRdd = sc.parallelize(largeList)
val pairs = wordsRdd.map(c => (c, 1))
                    .groupByKey()
                    .toDebugString

//pairs: String =
//(8) ShuffledRDD[219] at groupByKey at <console>:38 []
// +- (8) MapPartitionsRDD[218] at map at <console>:37 []
//      | ParallelCollectionRDD[217] at parallelize at <console>:36 []
```

# Lineages and Fault Tolerance

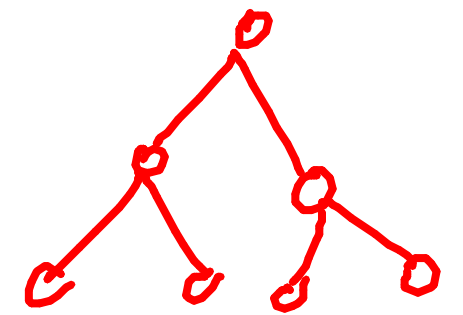
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Ideas from **functional programming** enable fault tolerance in Spark:

- ▶ RDDs are immutable.
- ▶ We use higher-order functions like map, flatMap, filter to do *functional* transformations on this immutable data.
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**Along with keeping track of dependency information between partitions as well, this allows us to:**

**Recover from failures by recomputing lost partitions from lineage graphs.**

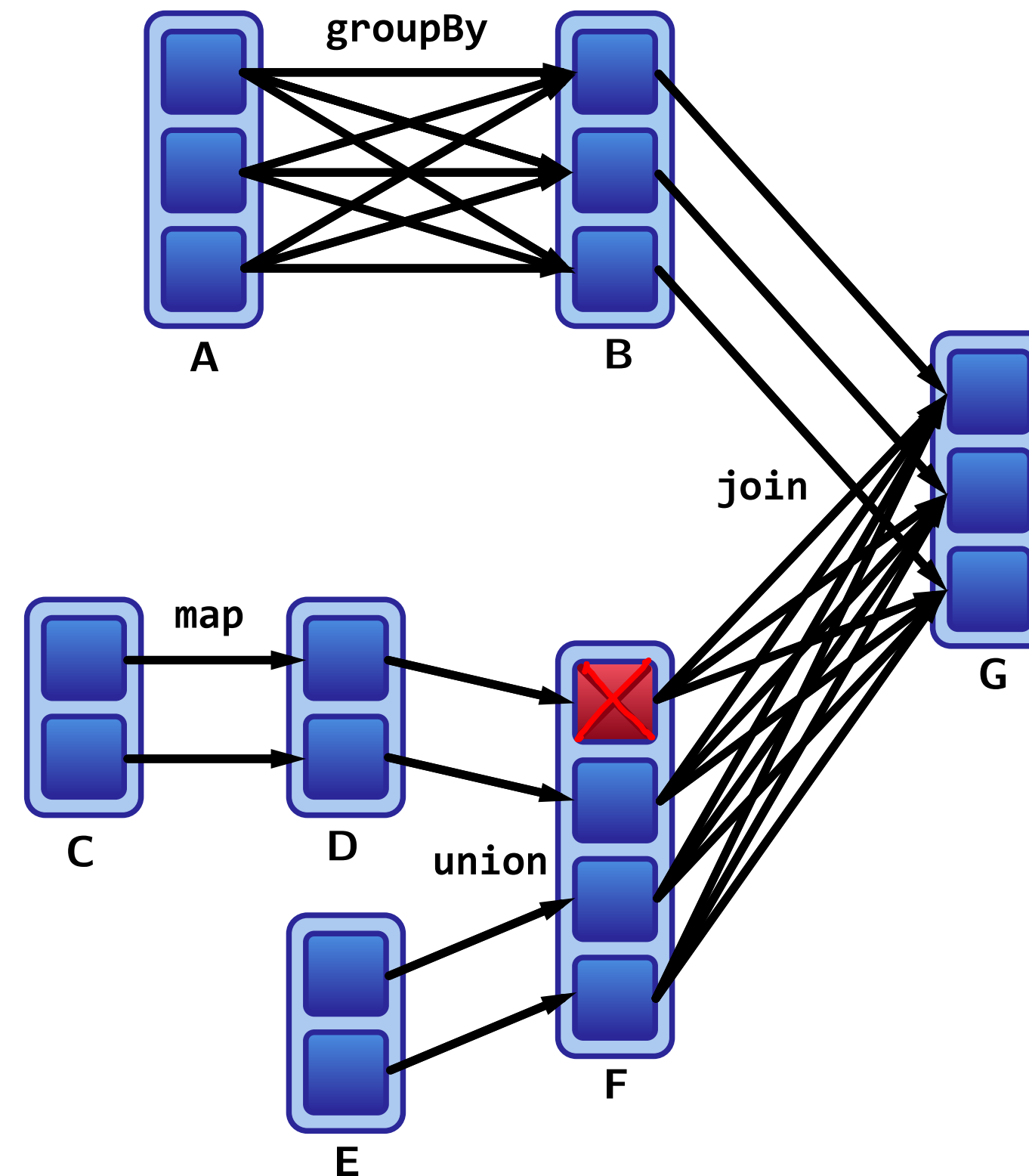
Fault tolerance  
w/out having  
to checkpoint  
& write data  
to disk!

in-memory  
+  
fault tolerant!

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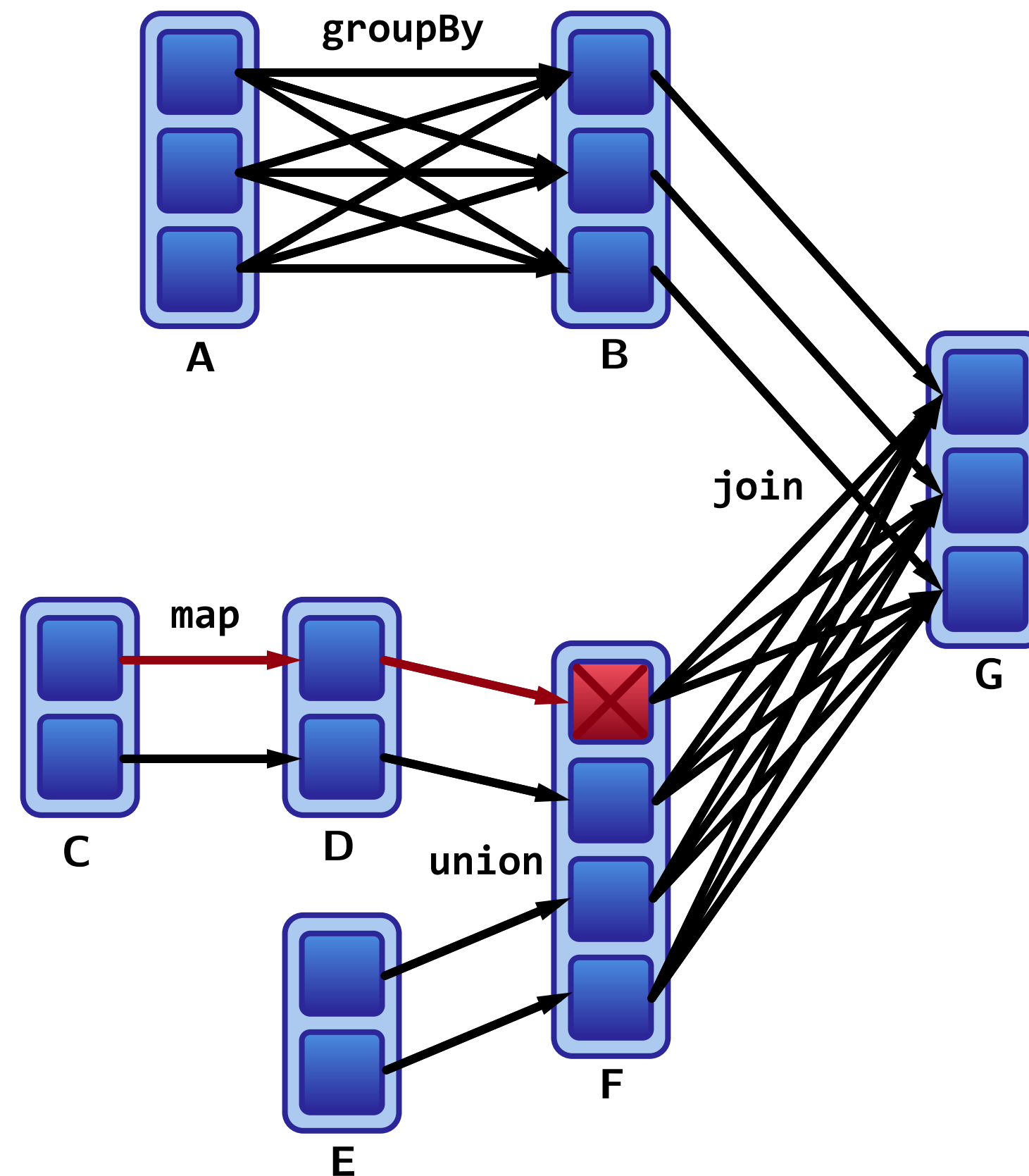
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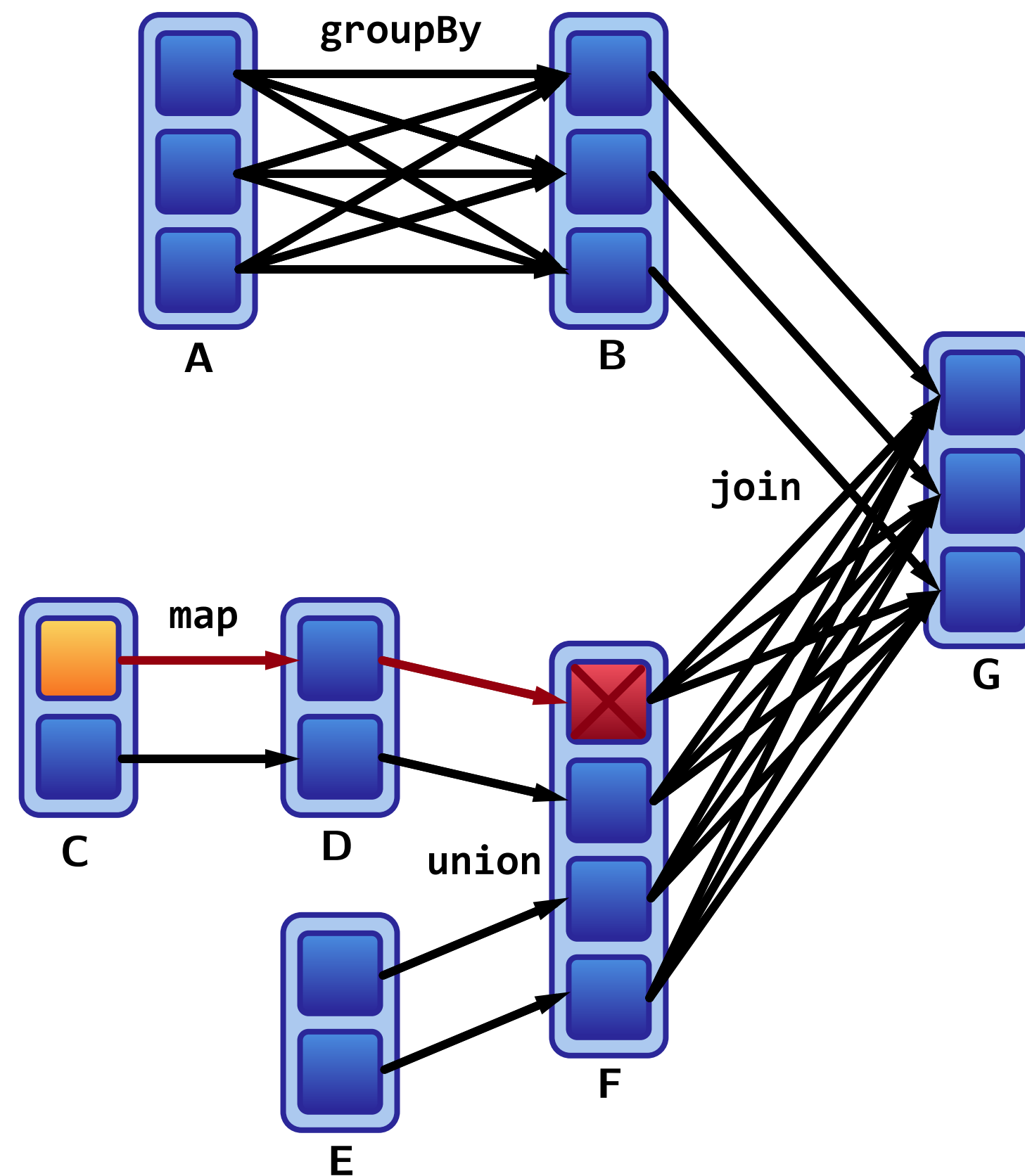
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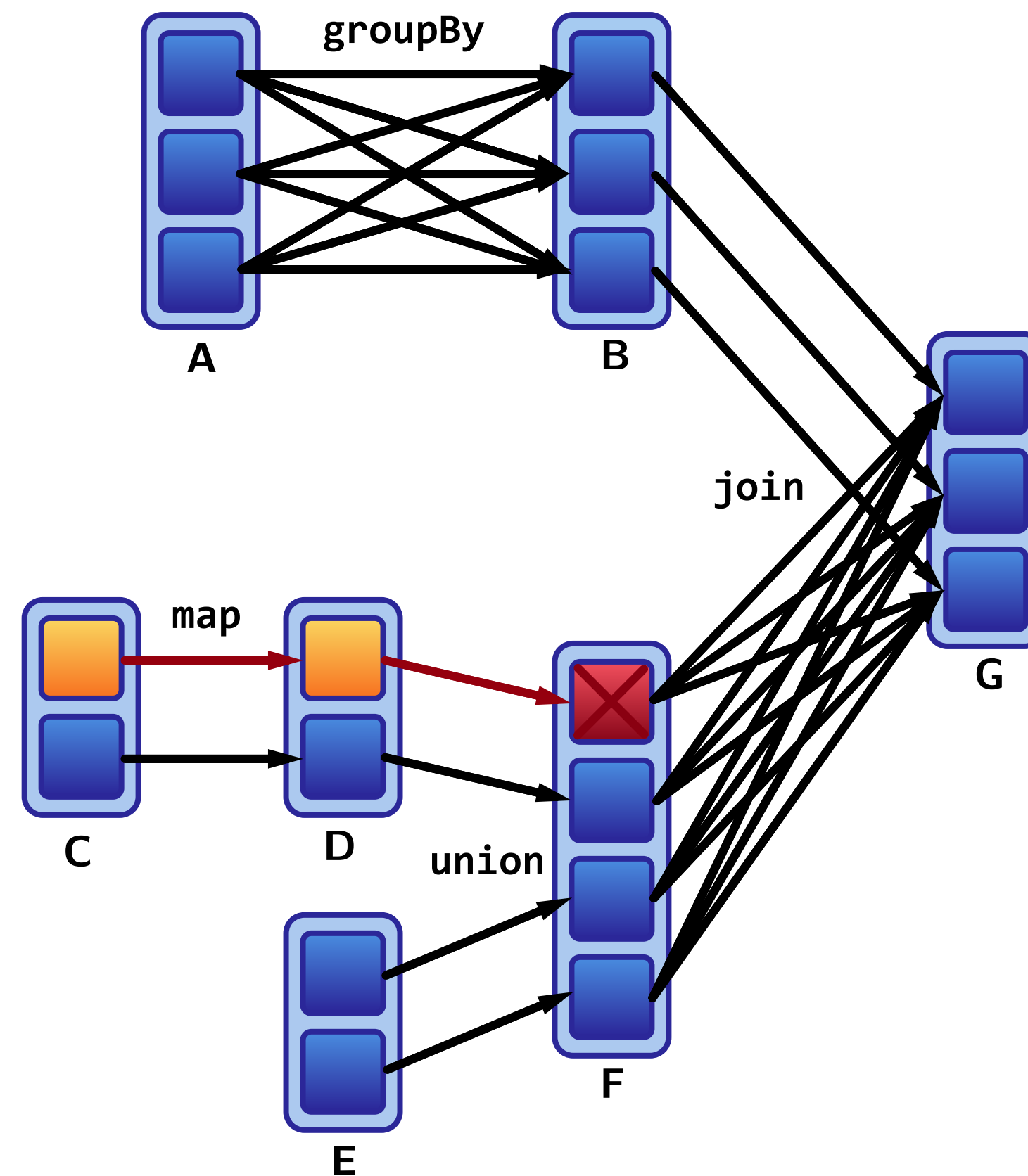
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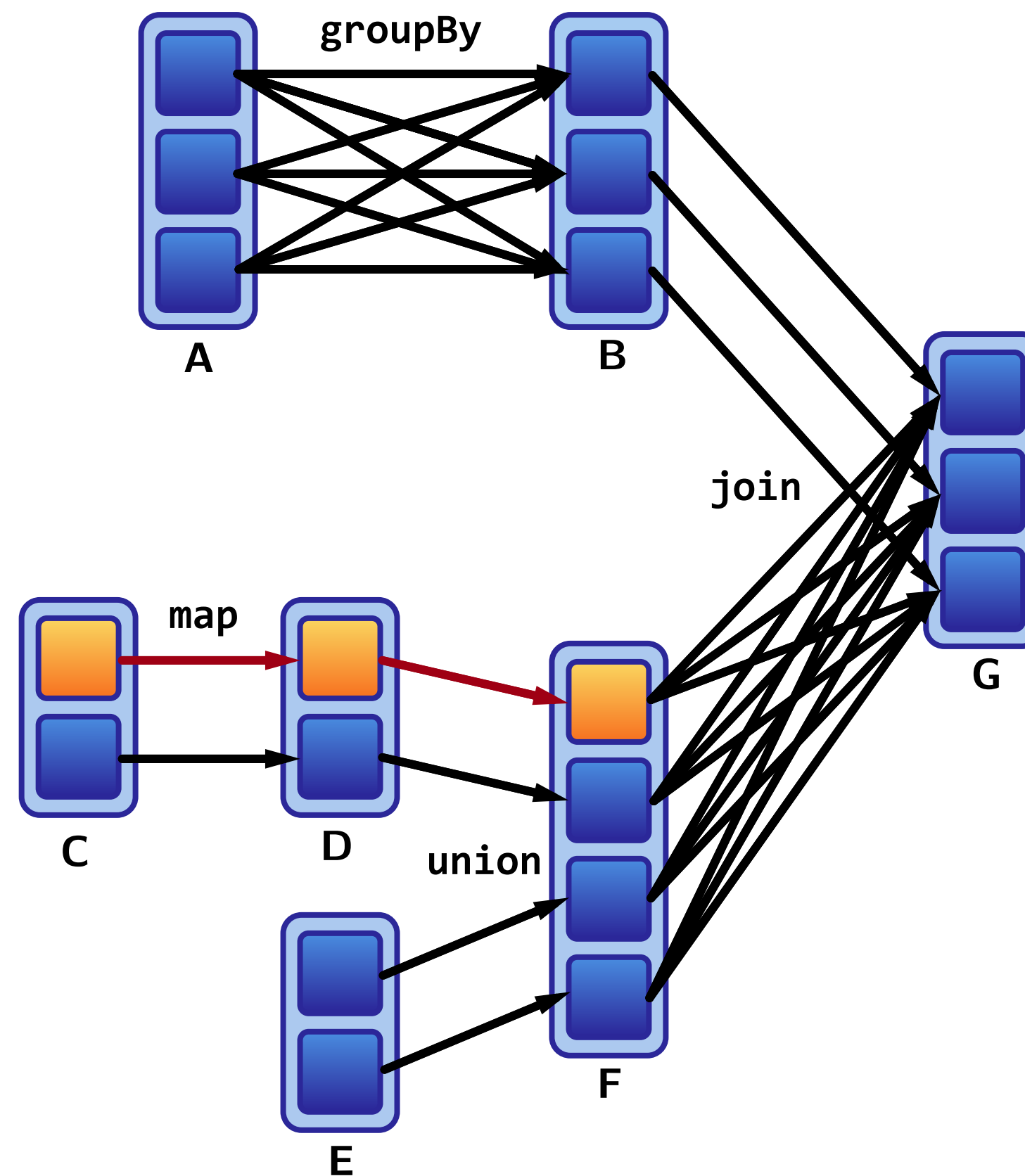
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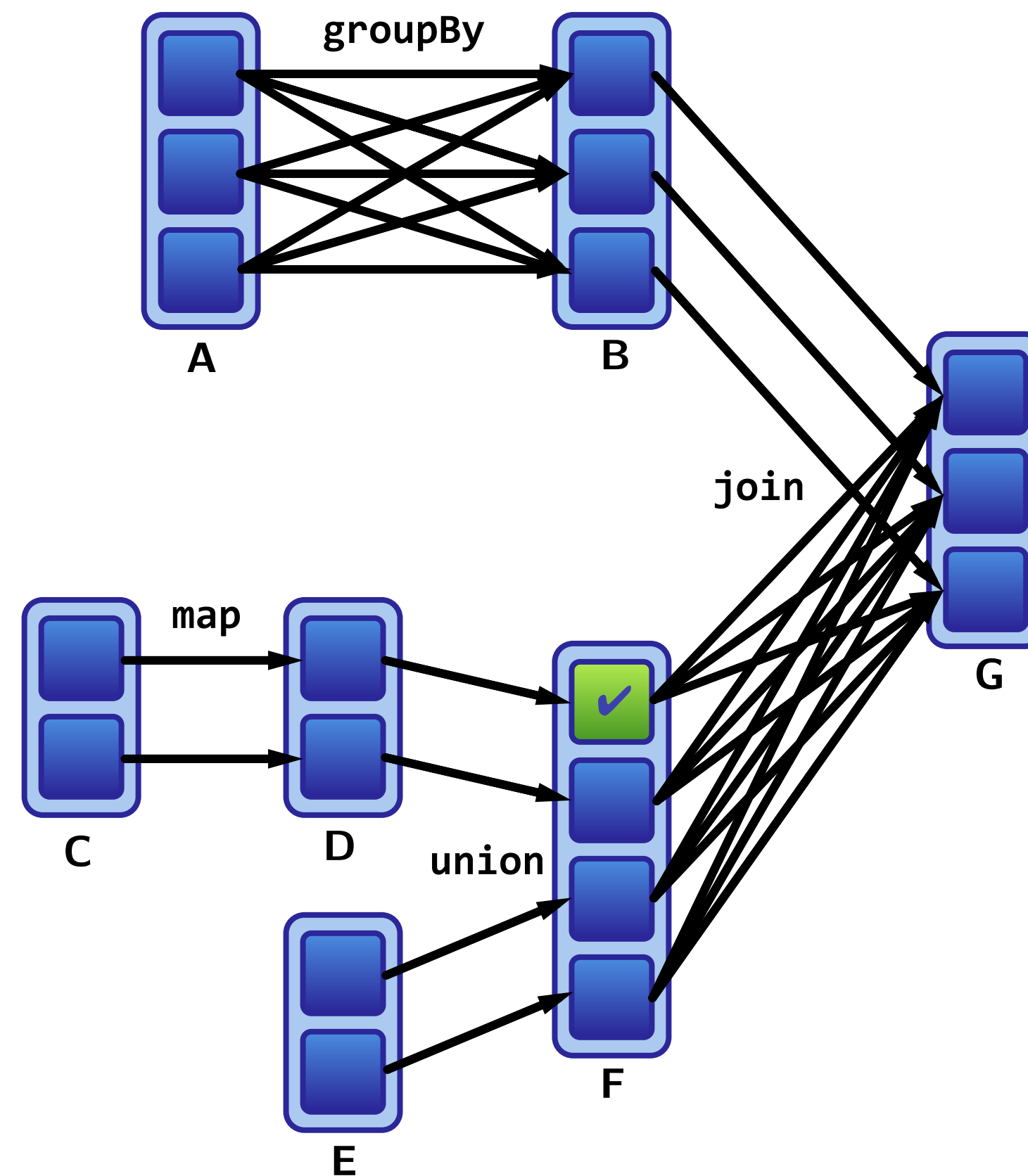
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