Wide vs Narrow Dependencies

Big Data Analysis with Scala and Spark

Heather Miller

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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.
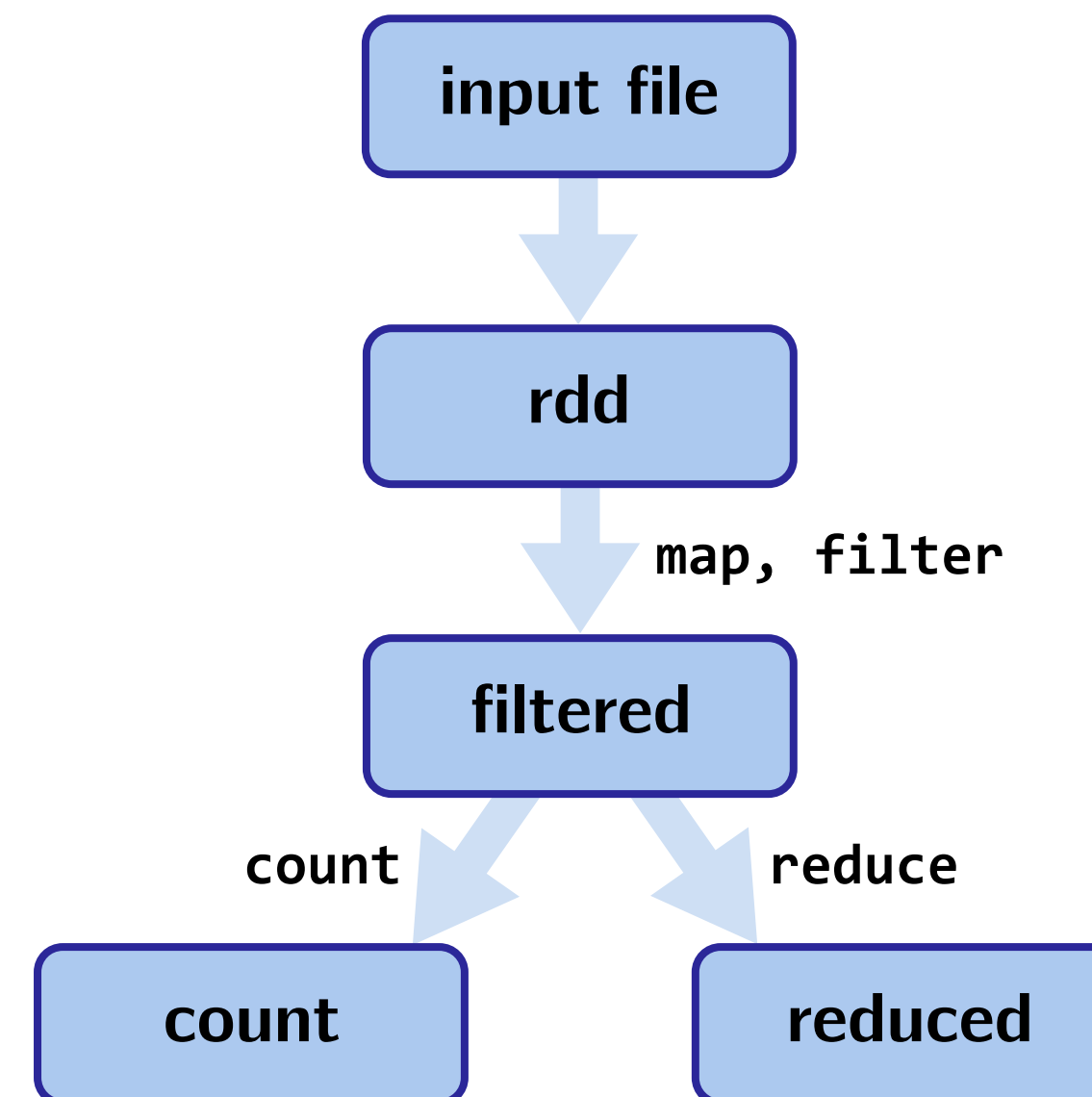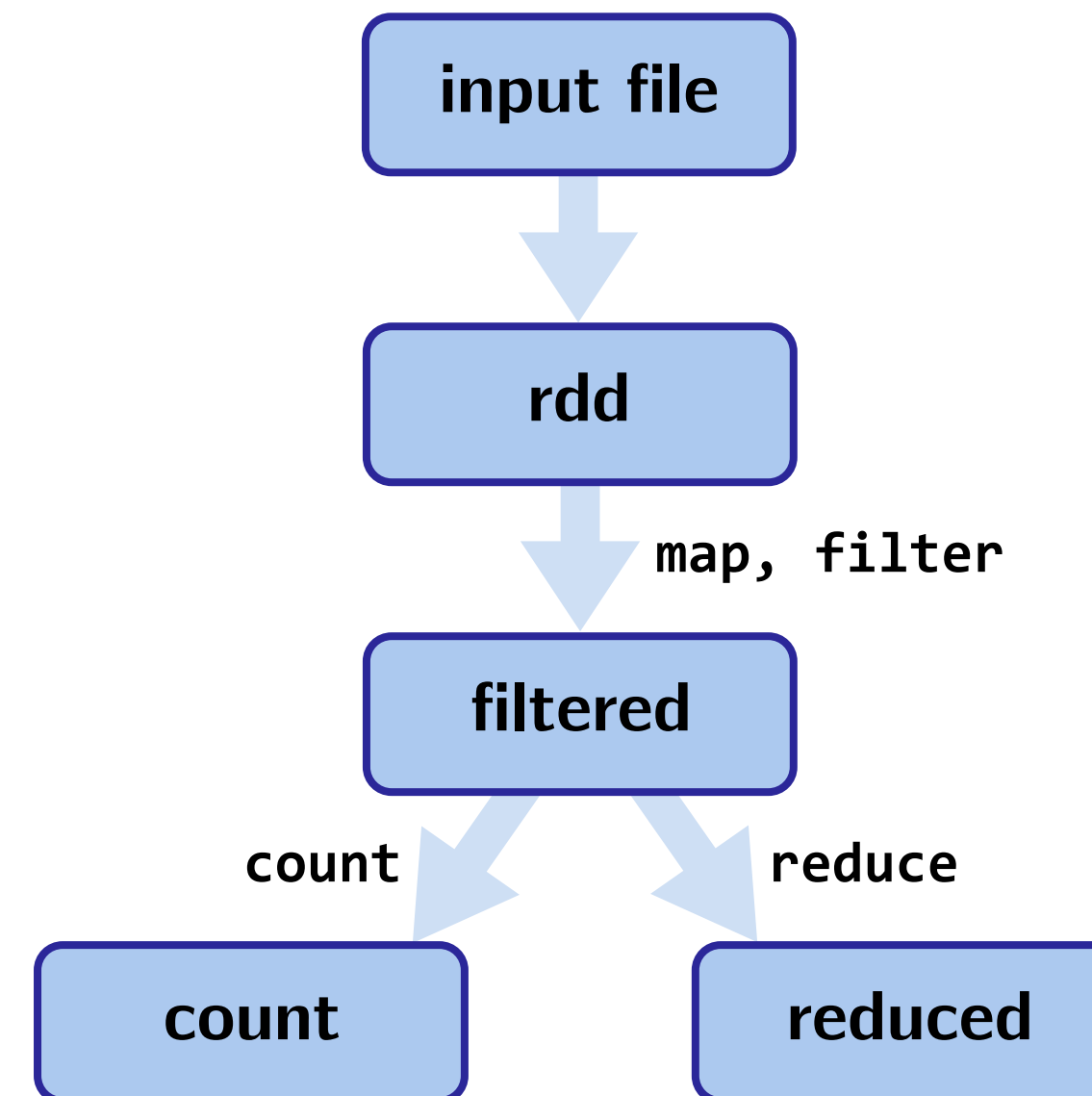
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Example:

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                  .filter(...)
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```
input file
    │
    ▼
   rdd
    │   map, filter
    ▼
 filtered
  count ╱   ╲ reduce
   ▼         ▼
 count     reduced
```
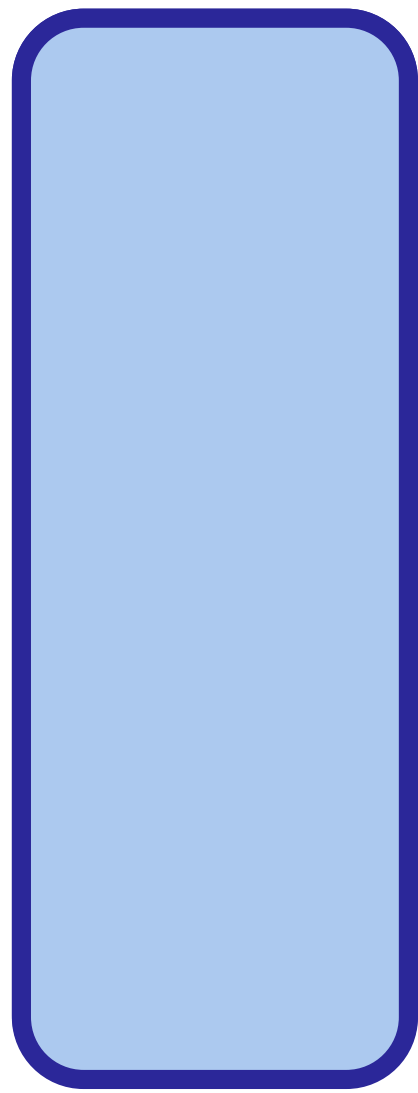
Spark represents RDDs in terms of these lineage graphs/DAGs
In fact, this is the representation/DAG is what Spark analyzes to do optimizations.

RDDs are made up of 2 important parts.
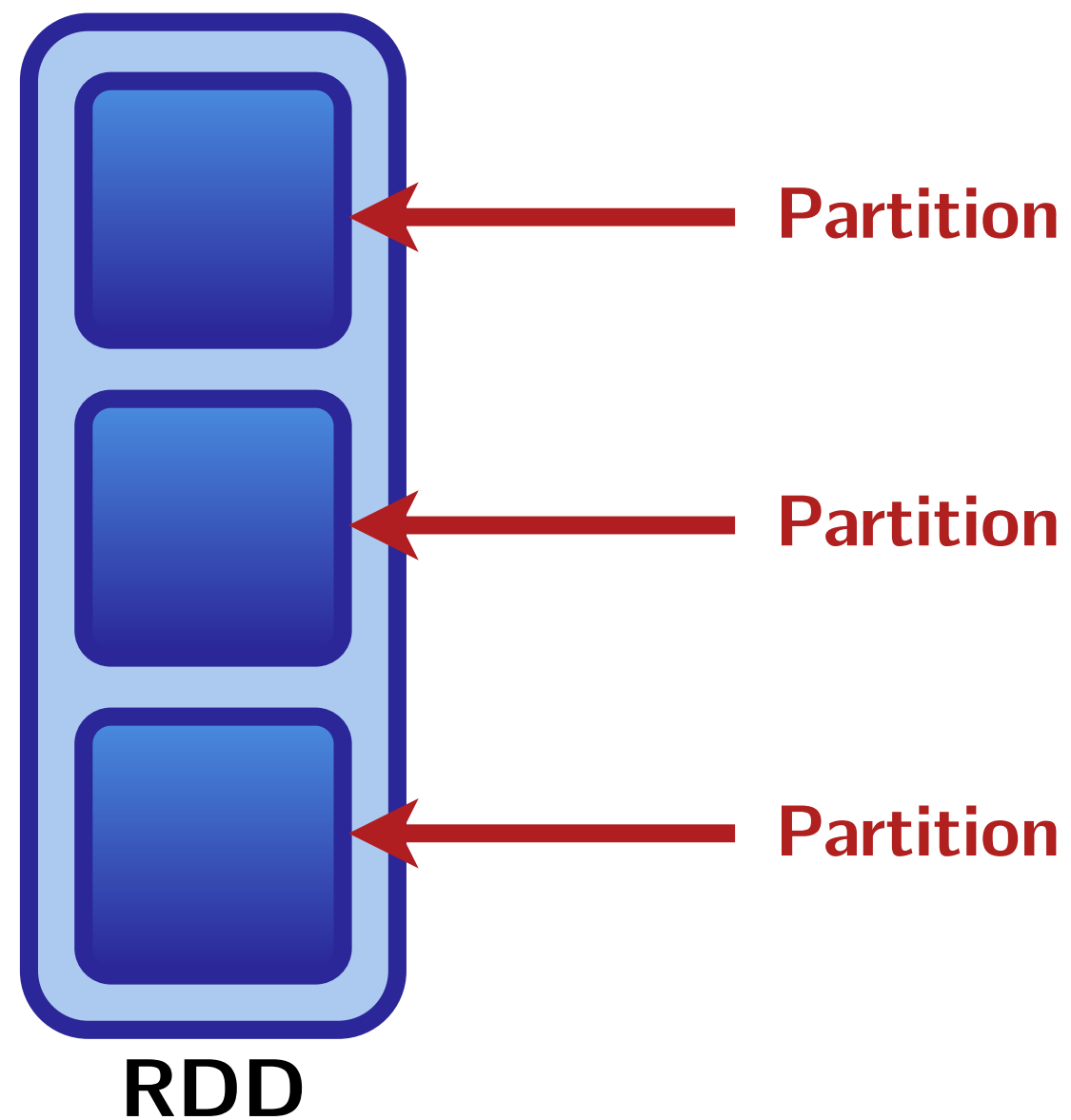*(but are made up of 4 parts in total)*

RDDs are represented as:

RDD

How are RDDs represented?

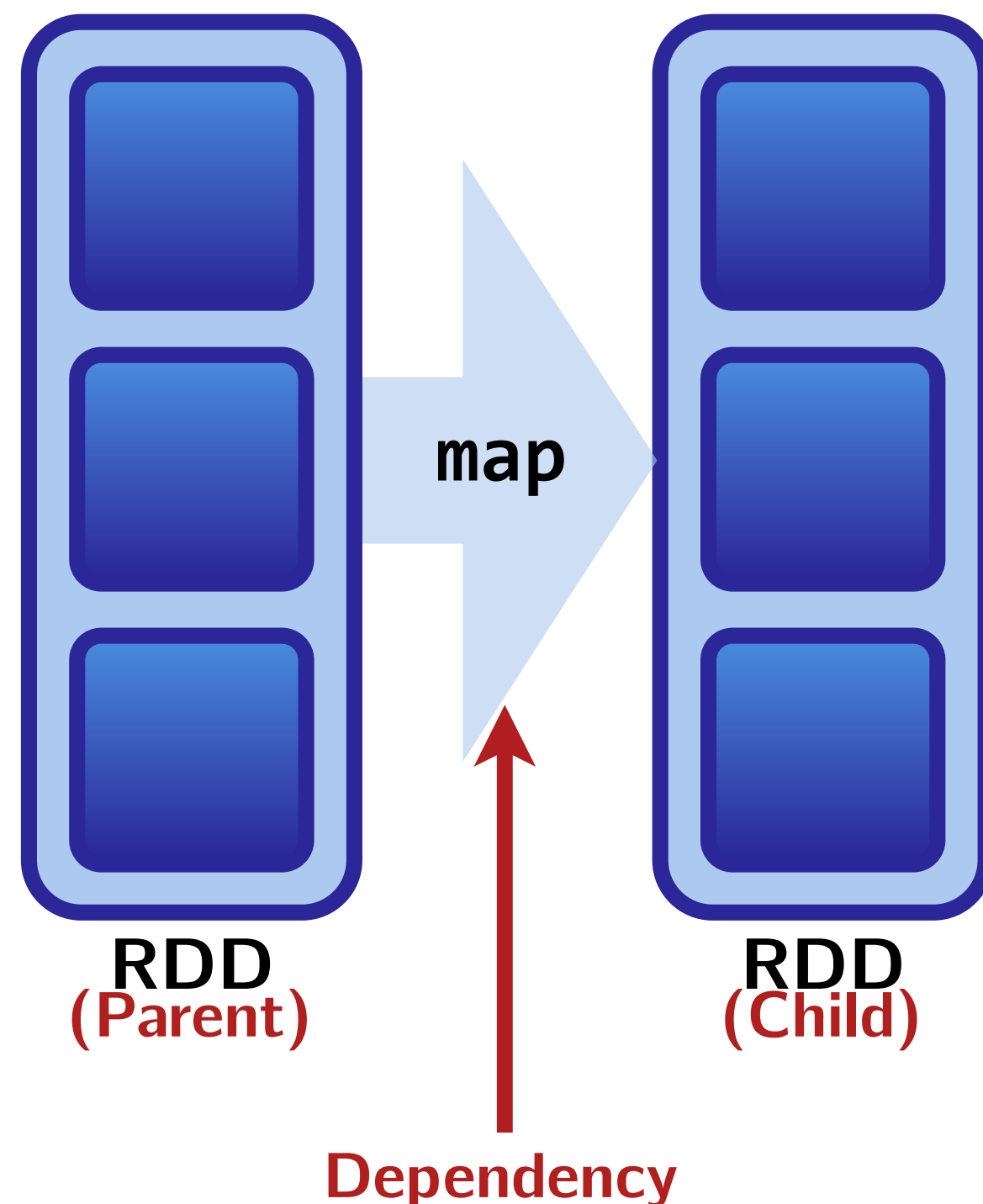RDDs are made up of 2 important parts.
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▸ **Partitions.** Atomic pieces of the dataset. One or many per compute node.

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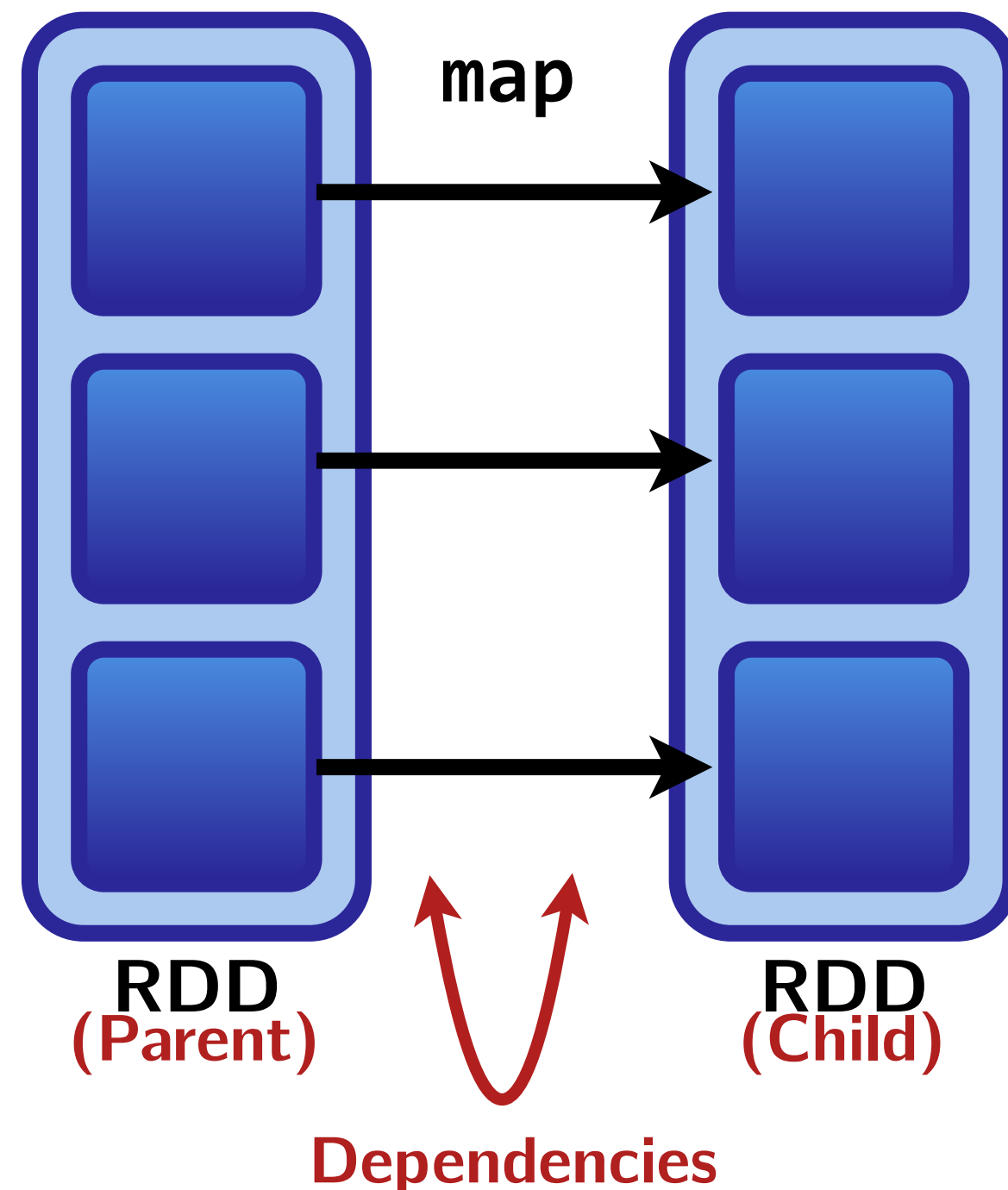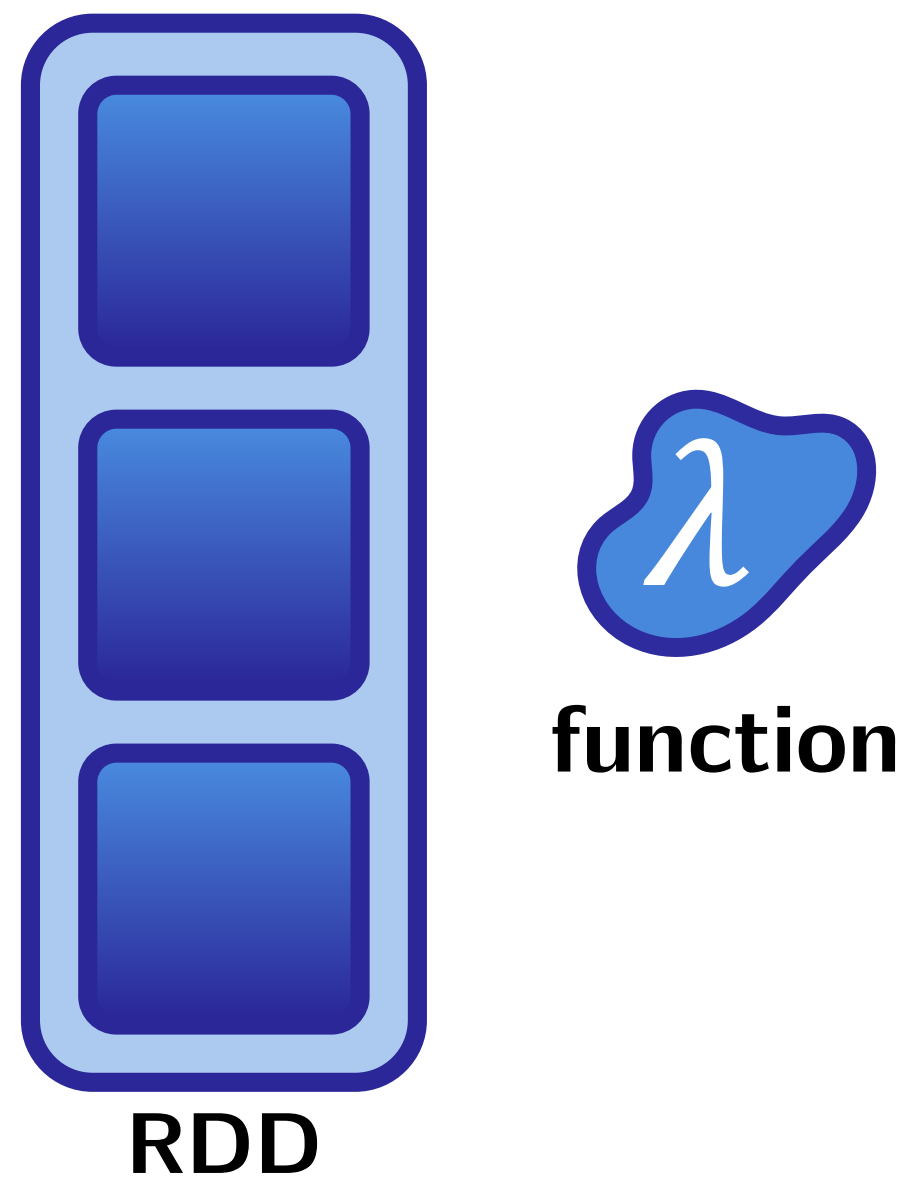

**RDD
(Parent)**

**RDD
(Child)**

map

Dependency

RDDs are represented as:

▸ **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.

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RDD (Parent)   **RDD (Child)**

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RDD

function

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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:

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

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

Narrow Dependencies vs Wide Dependences

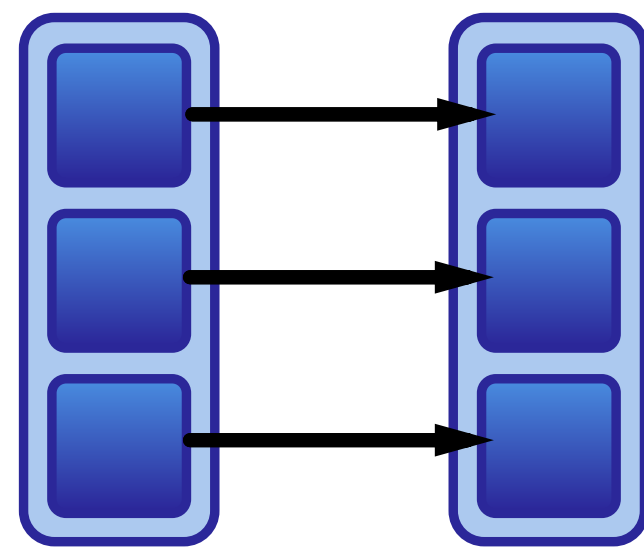**Narrow Dependencies**

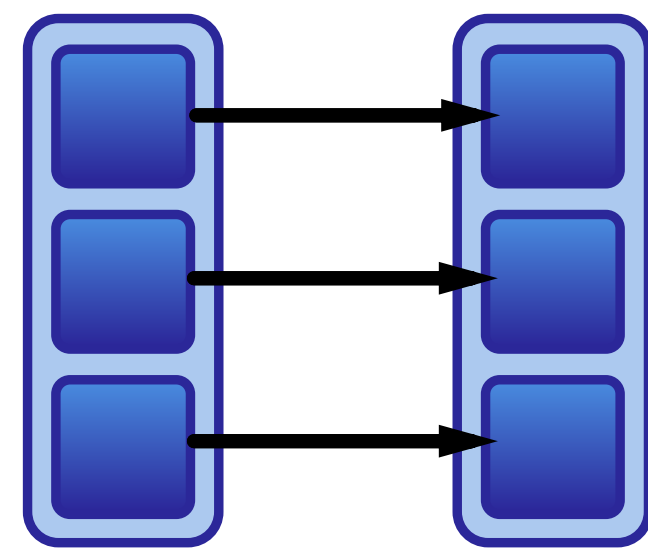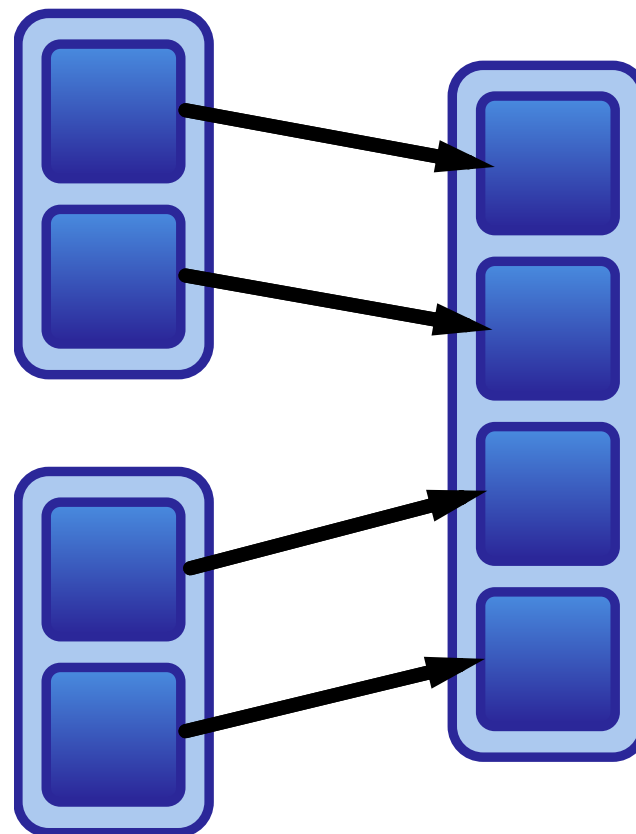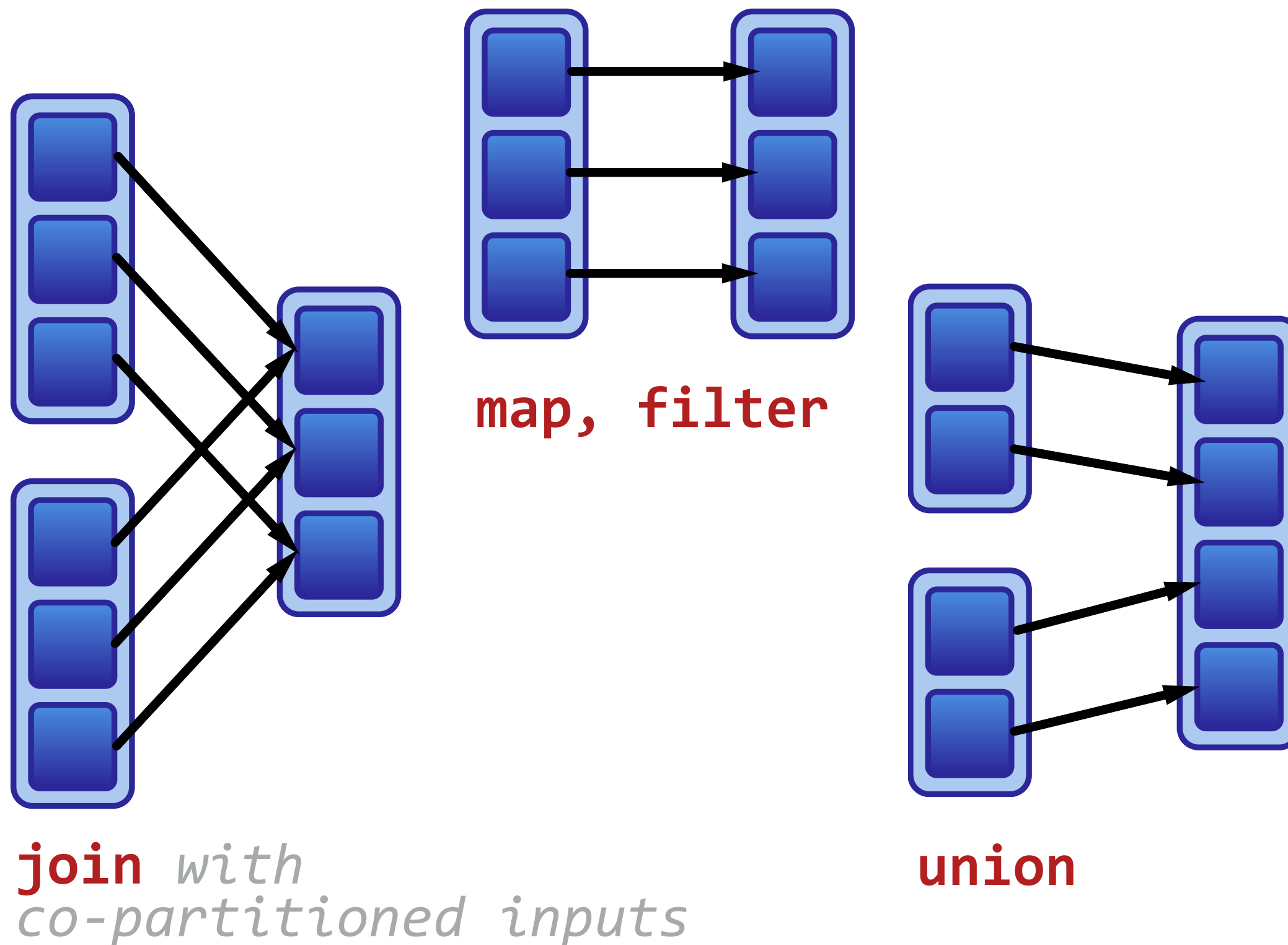Each partition of the parent RDD is used by at most one partition of the child RDD.

Wide Dependencies

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

Narrow Dependencies

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.

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join *with*
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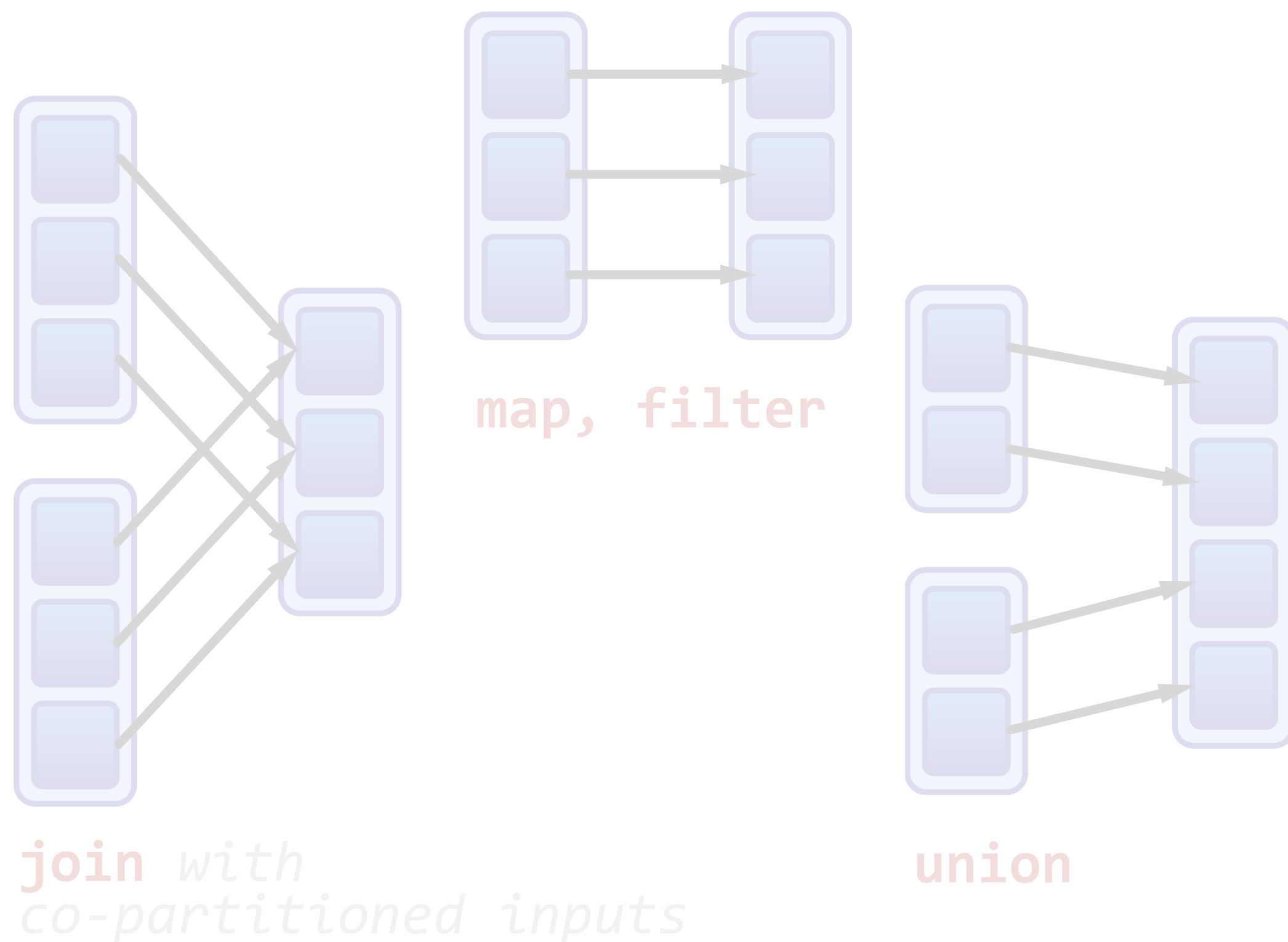**join** *with co-partitioned inputs*

union

Wide dependencies:

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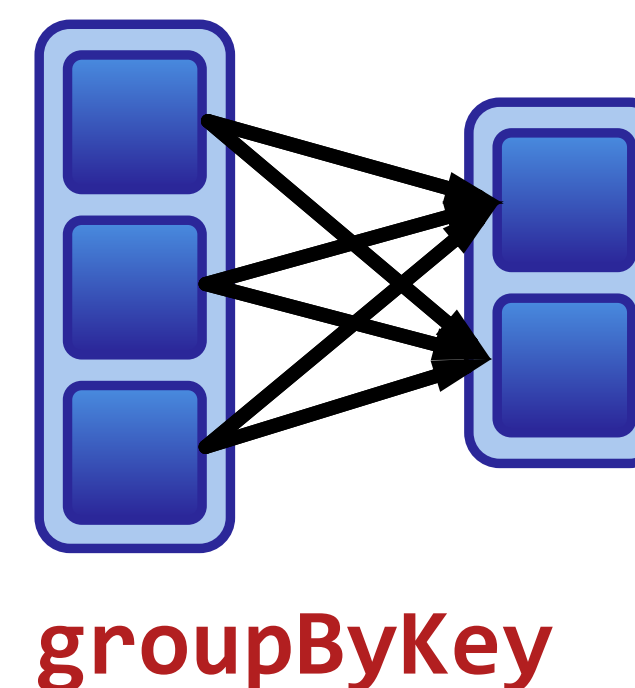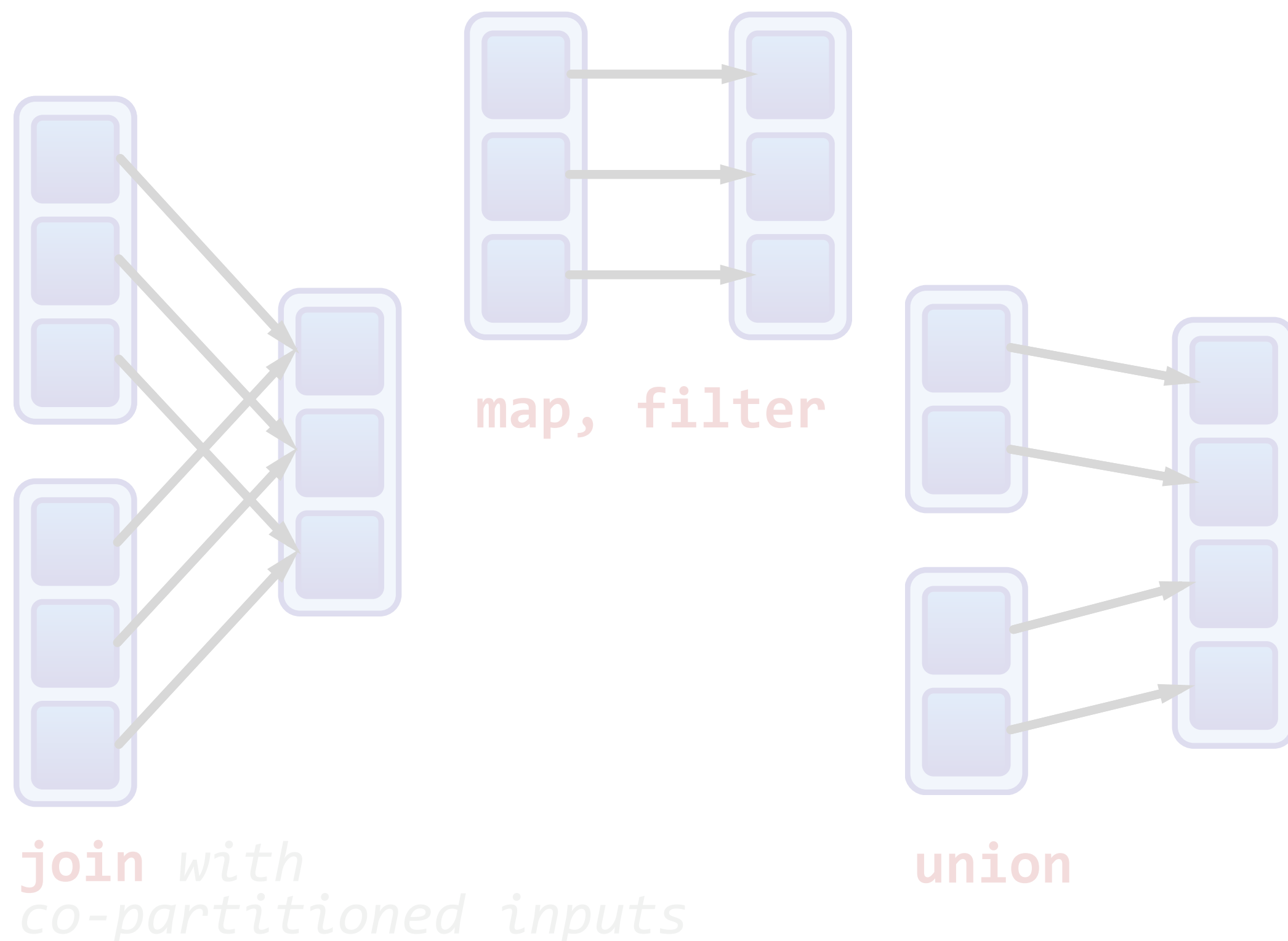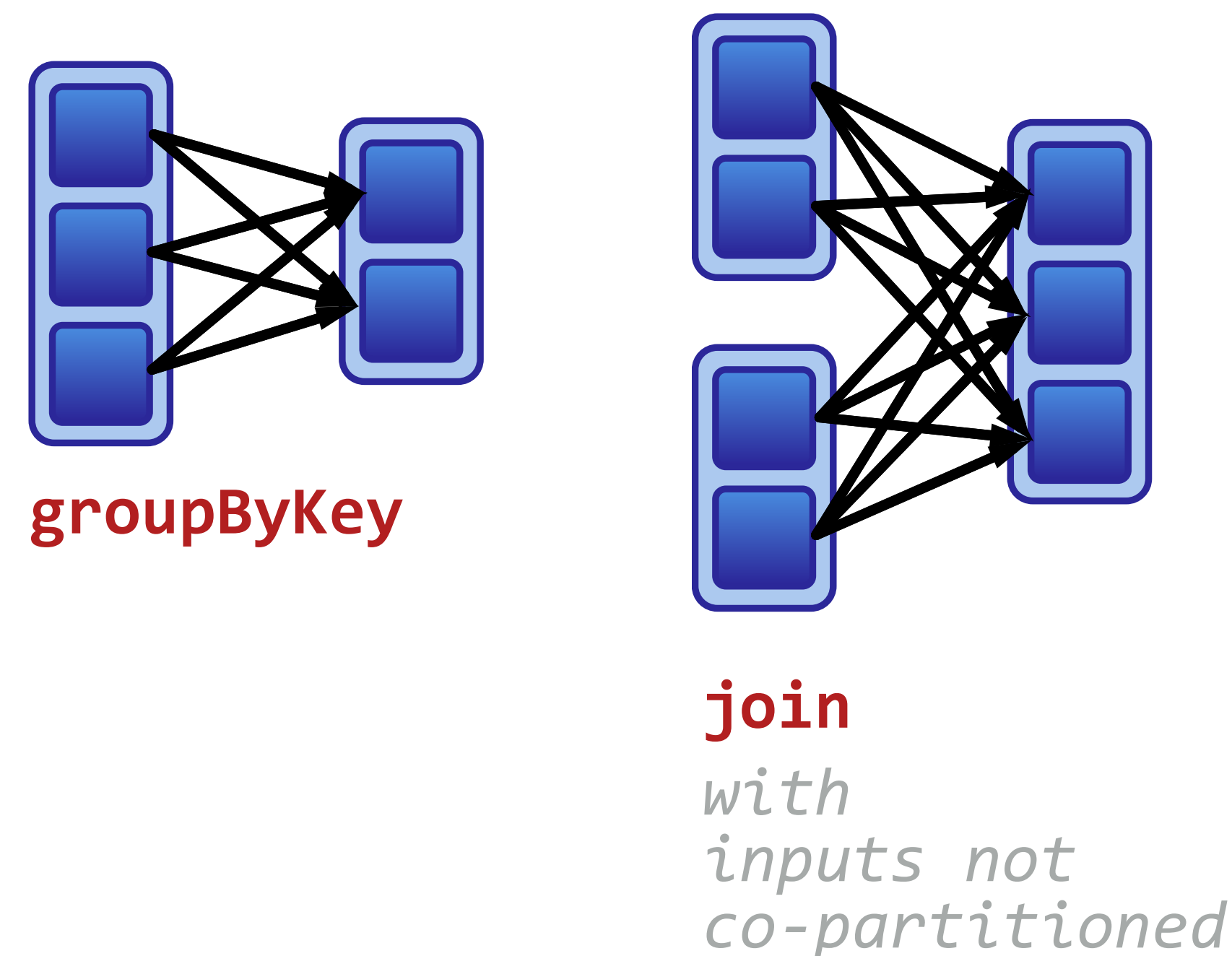# Narrow Dependencies vs Wide Dependences, Visually

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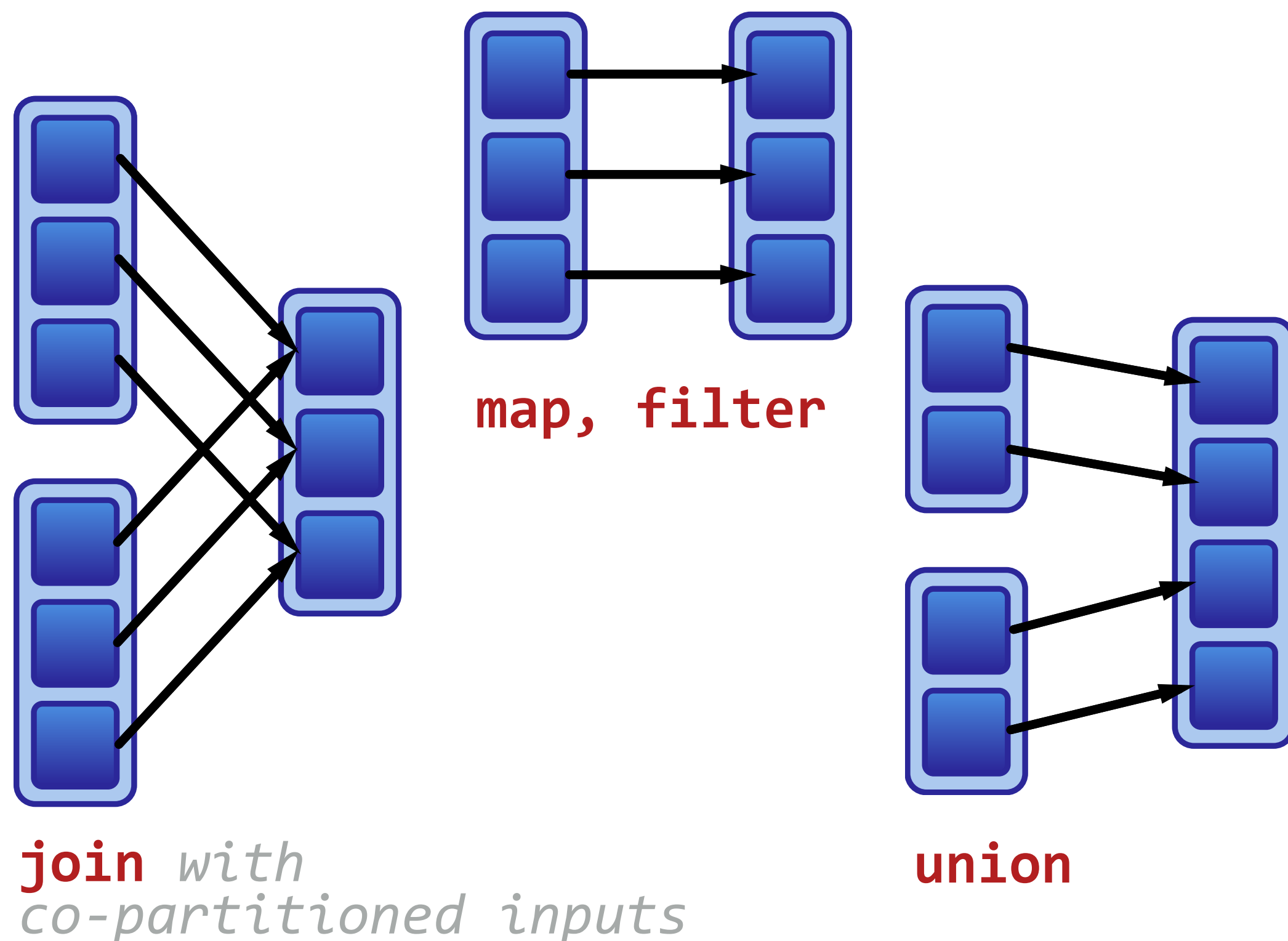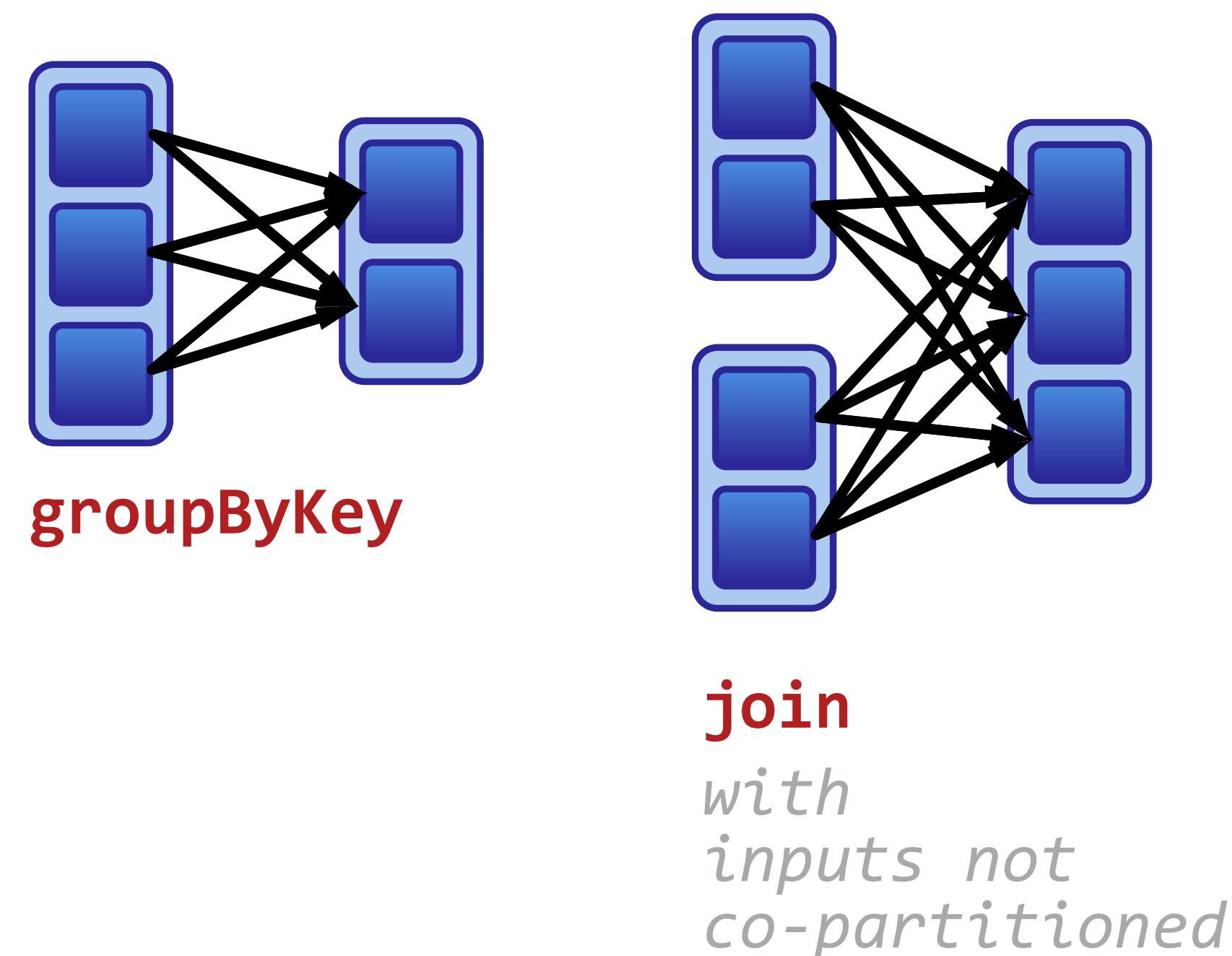
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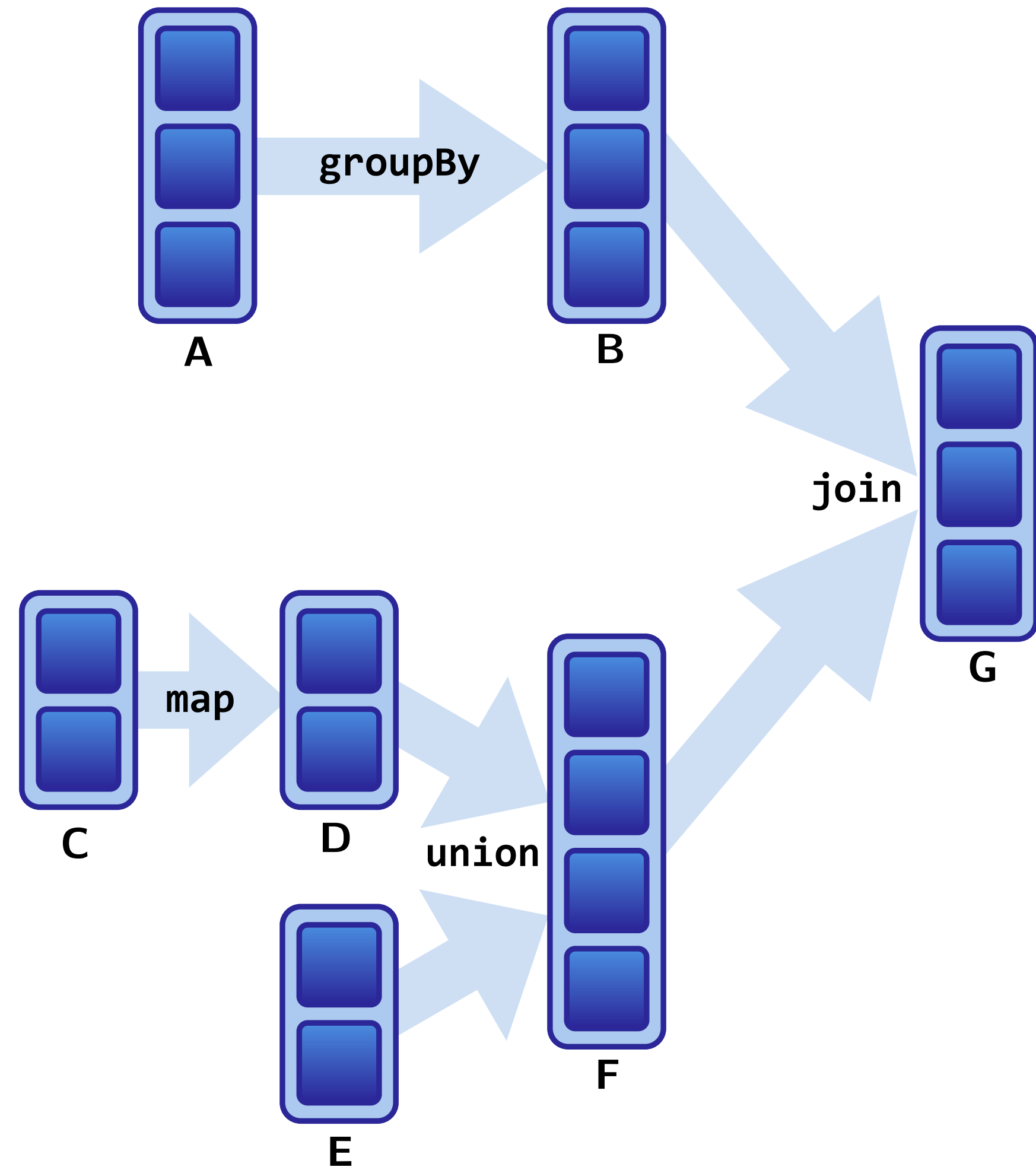

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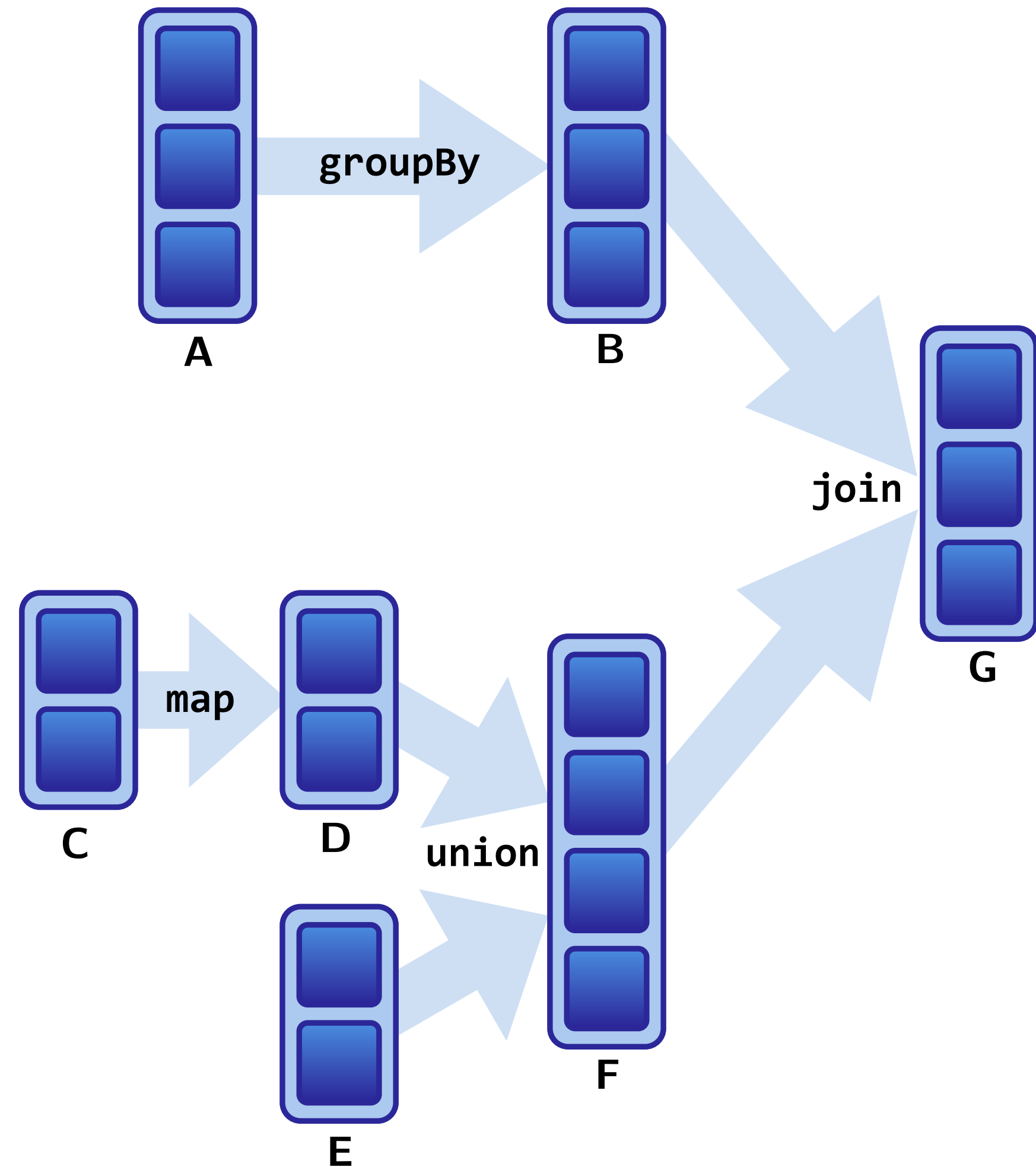
Narrow Dependencies vs Wide Dependences, Visually

Let's visualize an example
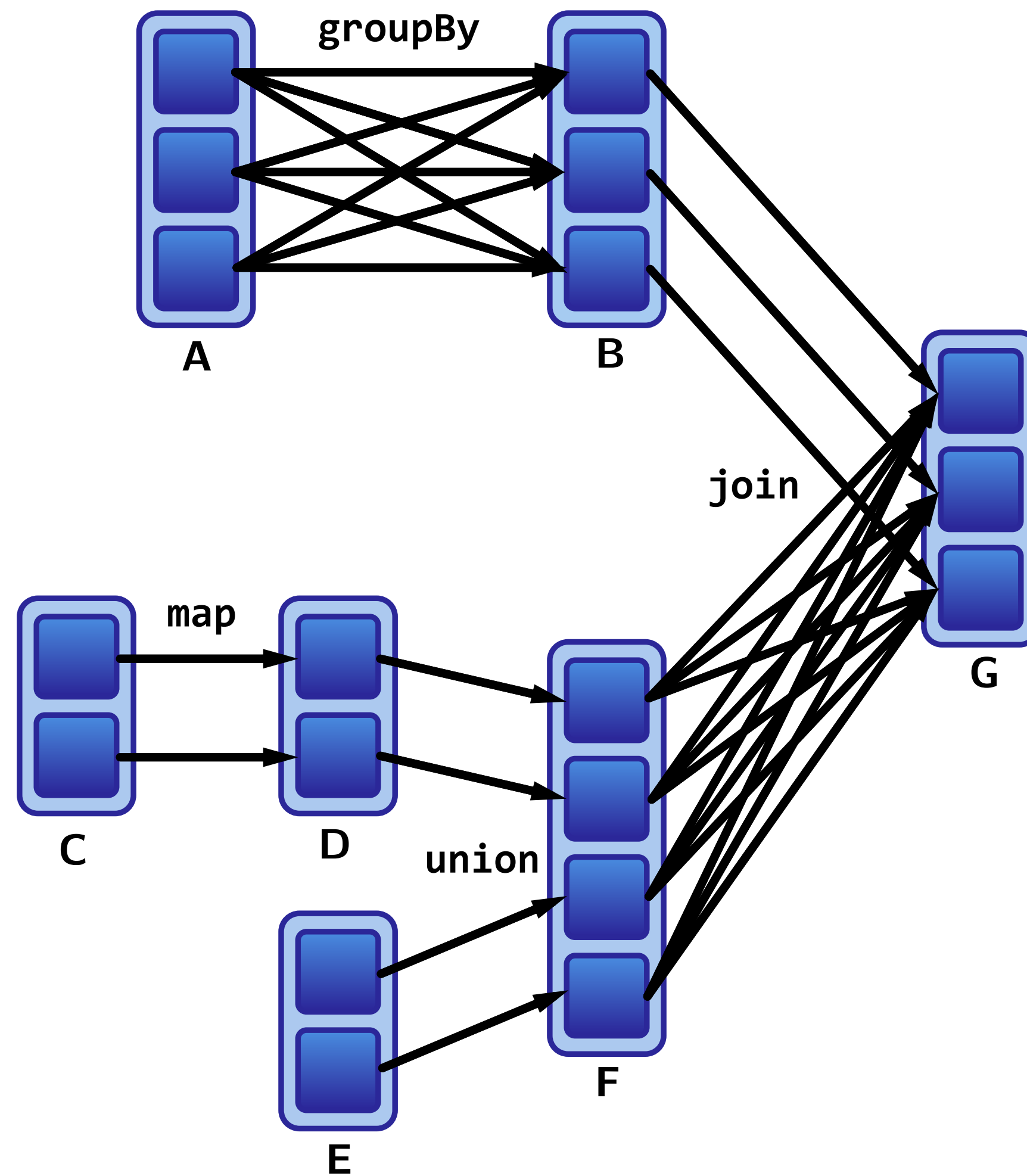program and its dependencies.

Let's visualize an example program and its dependencies.

Conceptually assuming the DAG:

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Conceptually assuming the DAG:

What do the dependencies look like?
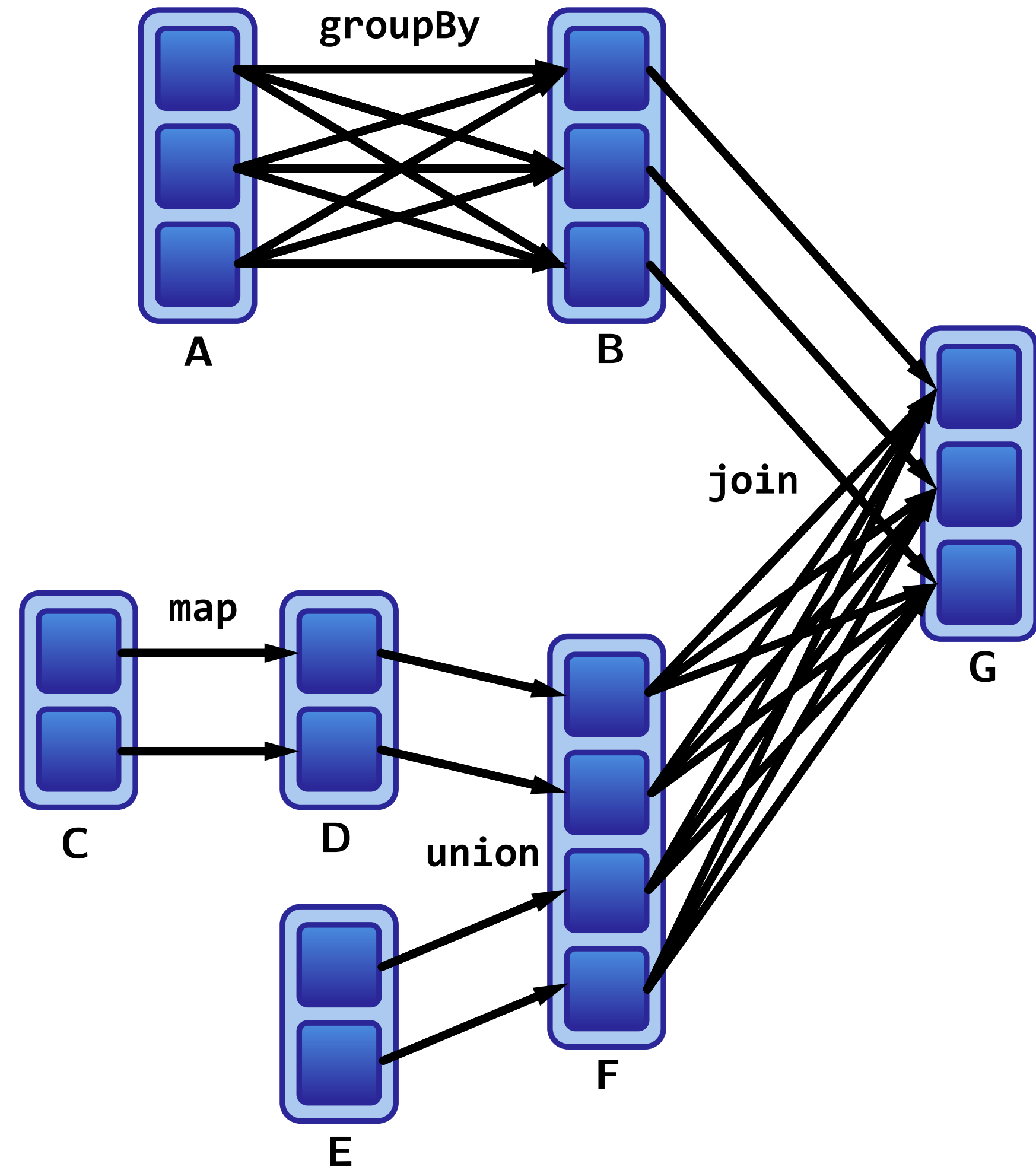
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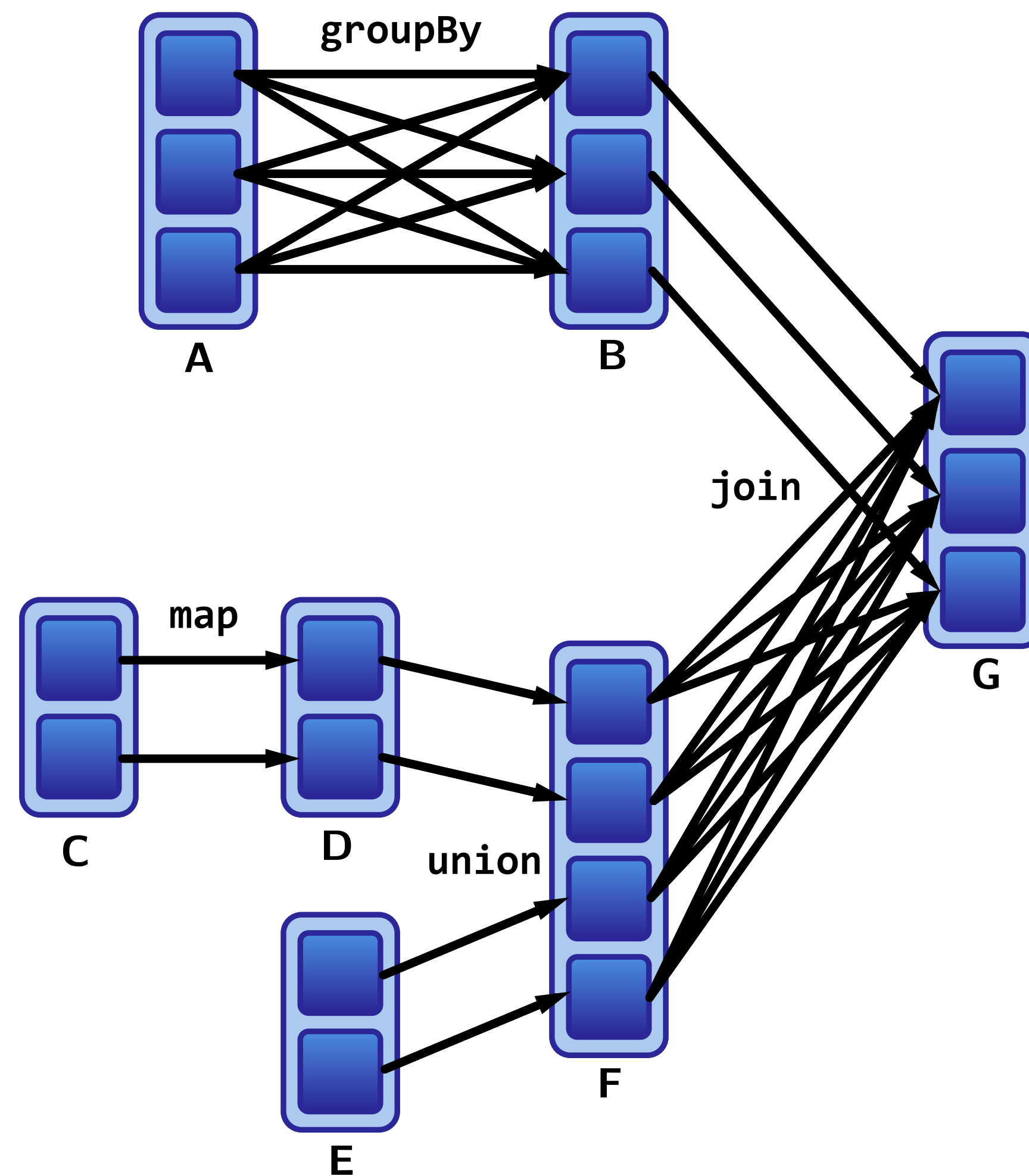
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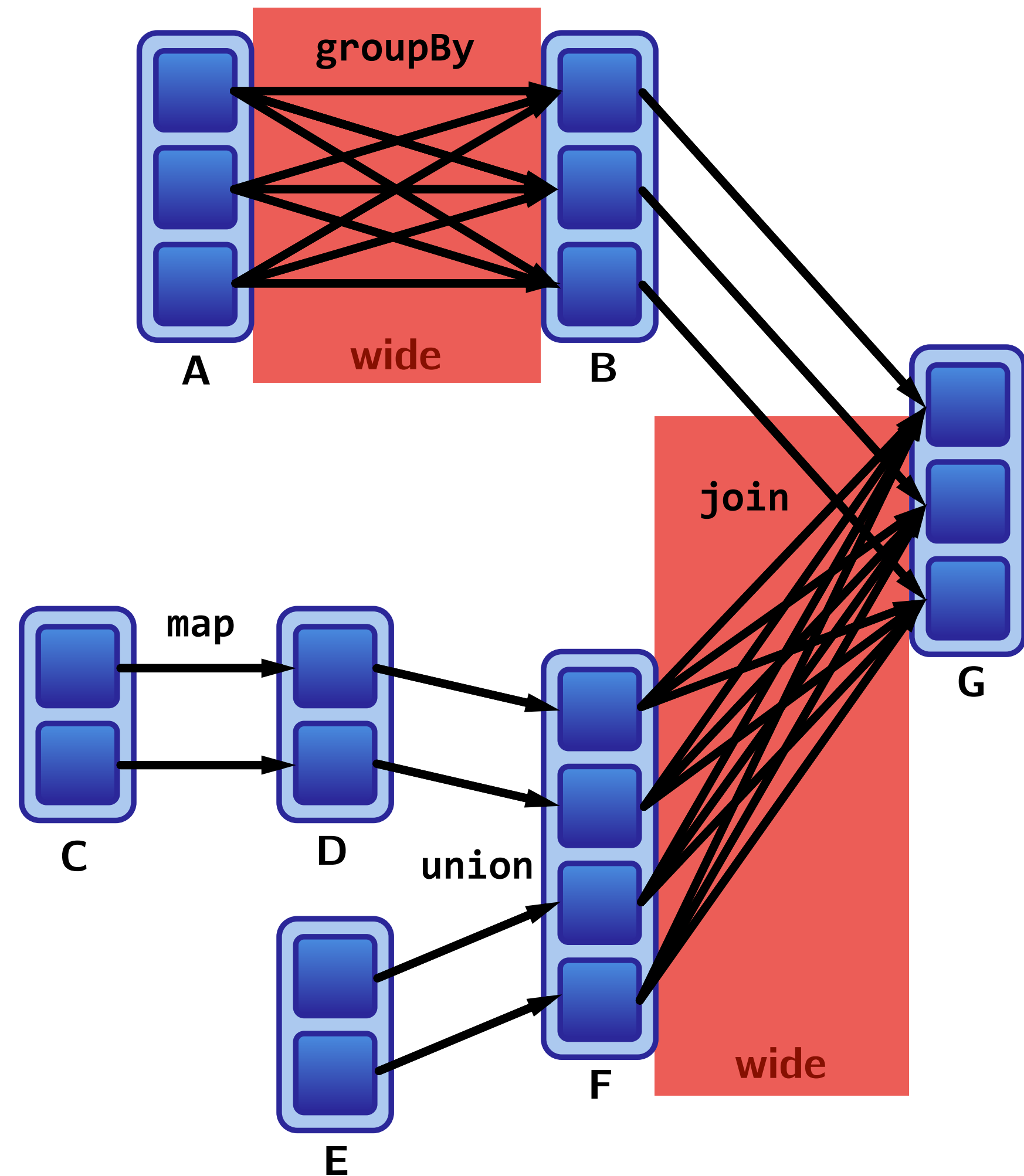
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`groupBy, join`

Narrow transformations:
`map, union, join`

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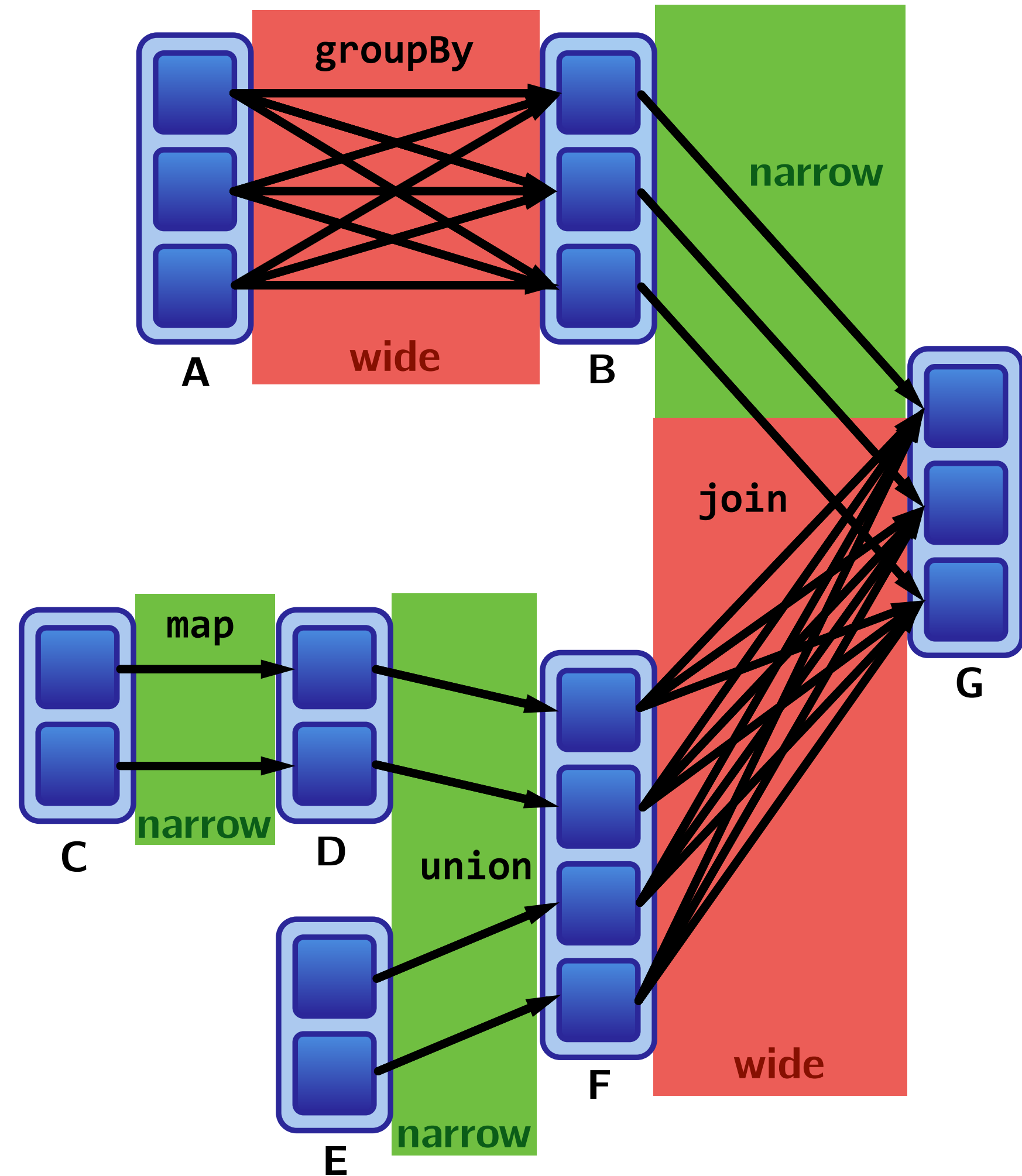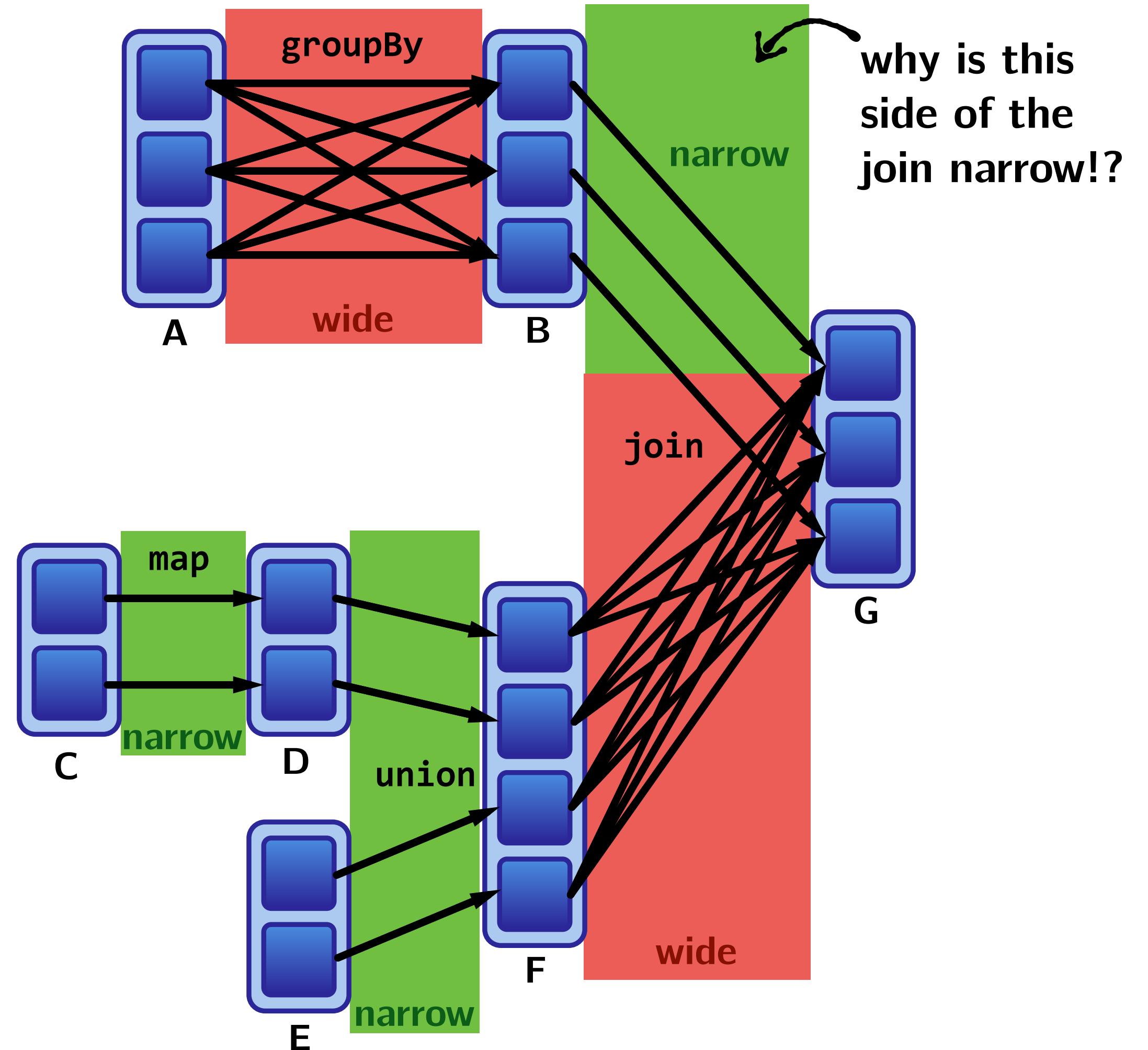
Wide transformations:
`groupBy, join`

Narrow transformations:
`map, union, join` ⚠️

groupBy

wide

A   B

narrow

why is this side of the join narrow!?

join

G

map
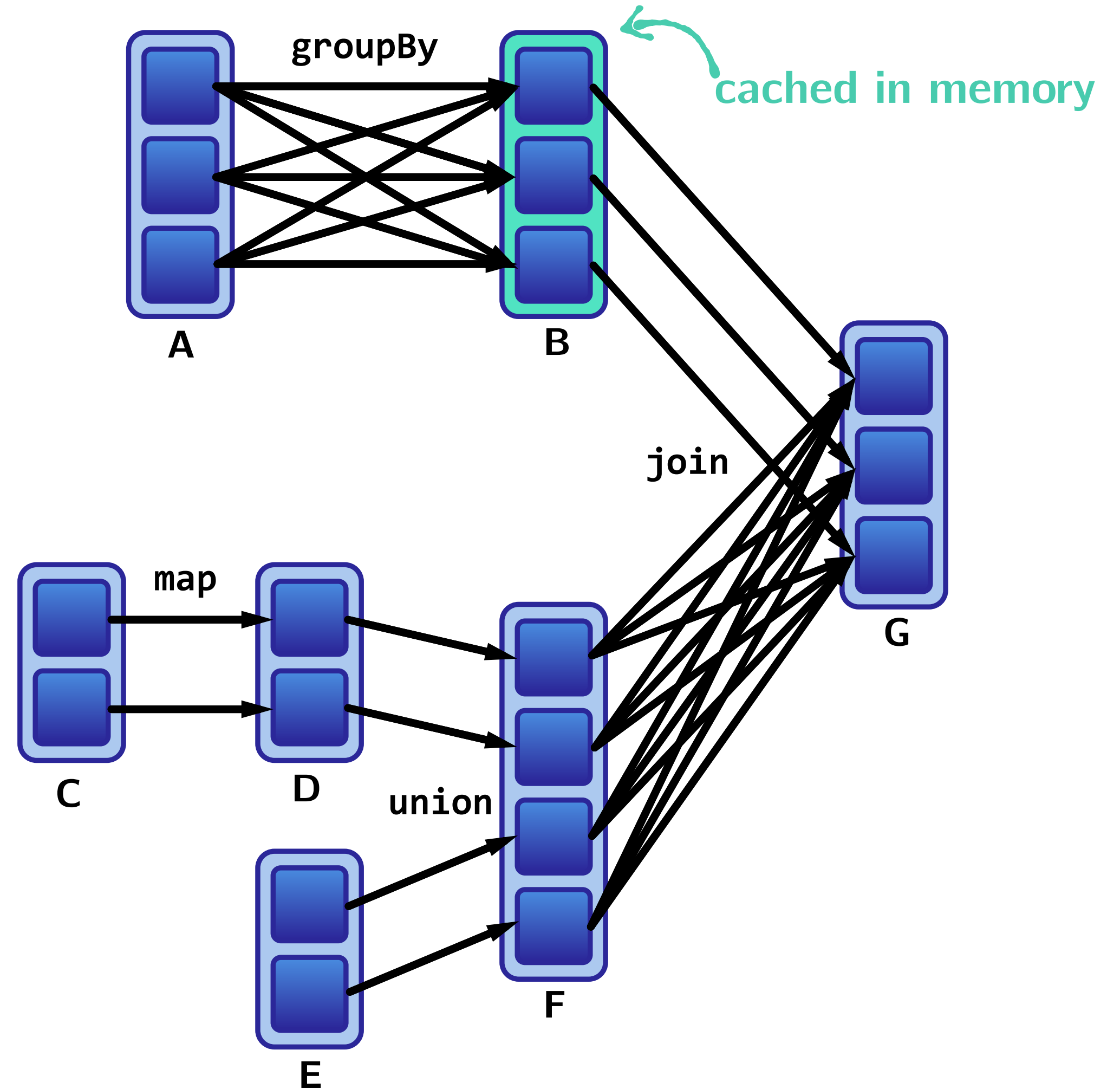
narrow

C   D

union

F

wide

E

narrow

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*.

```scala
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 []
```
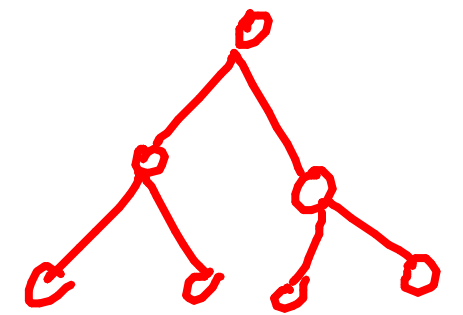
Lineages and Fault Tolerance

Lineages graphs are the key to fault tolerance in Spark.

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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.
- ▶ A function for computing the dataset based on its parent RDDs also
  is part of an RDD's representation.

Lineages and Fault Tolerance

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

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in-memory & fault tolerant!

Along with keeping track of dependency information between partitions as well, this allows us to:

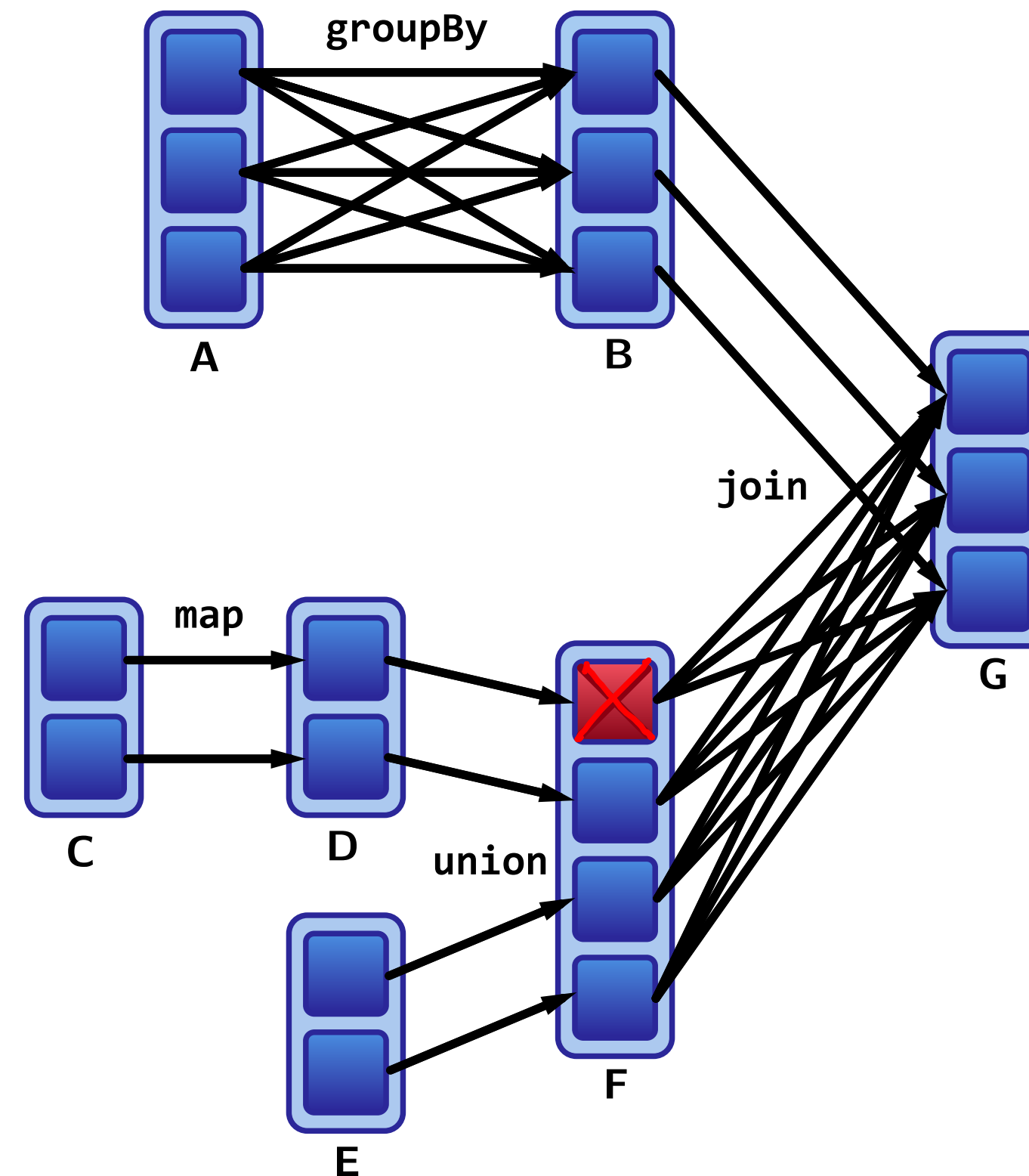> **Recover from failures by recomputing lost partitions from lineage graphs.**

Lineages graphs are the key to fault tolerance in Spark.

Let's assume one of our partitions from our previous example fails.

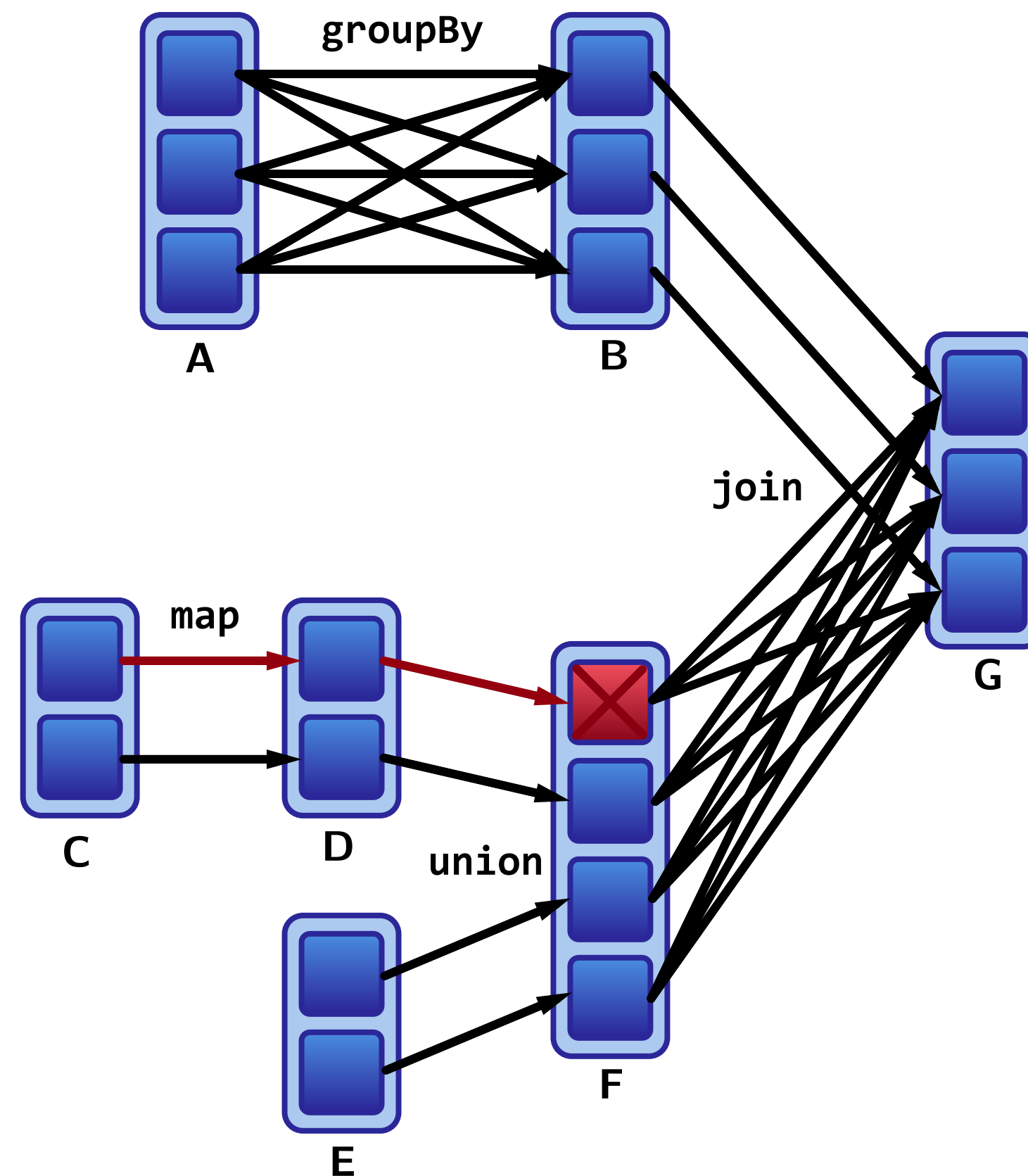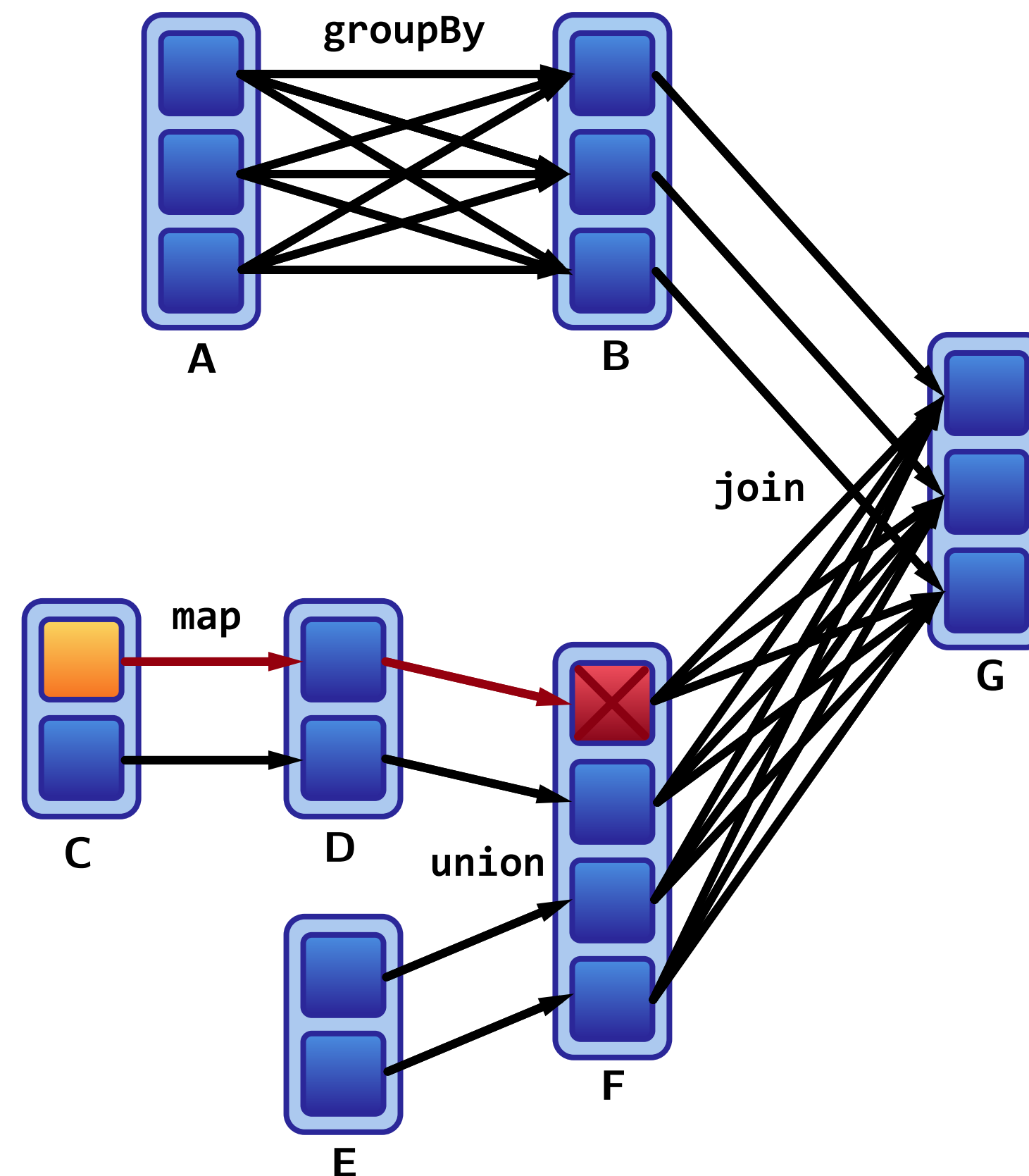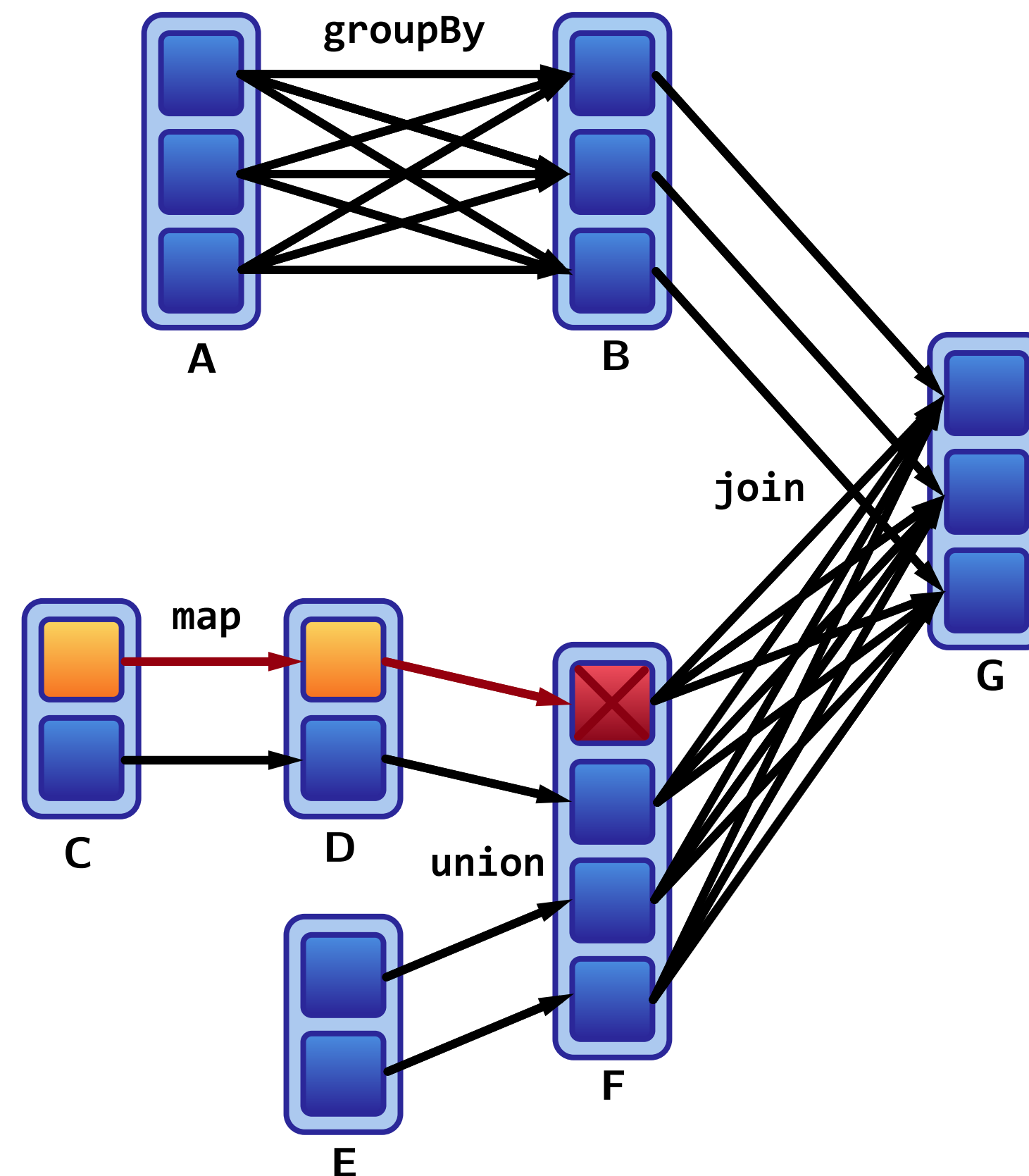**Lineages graphs are the key to fault tolerance in Spark.**

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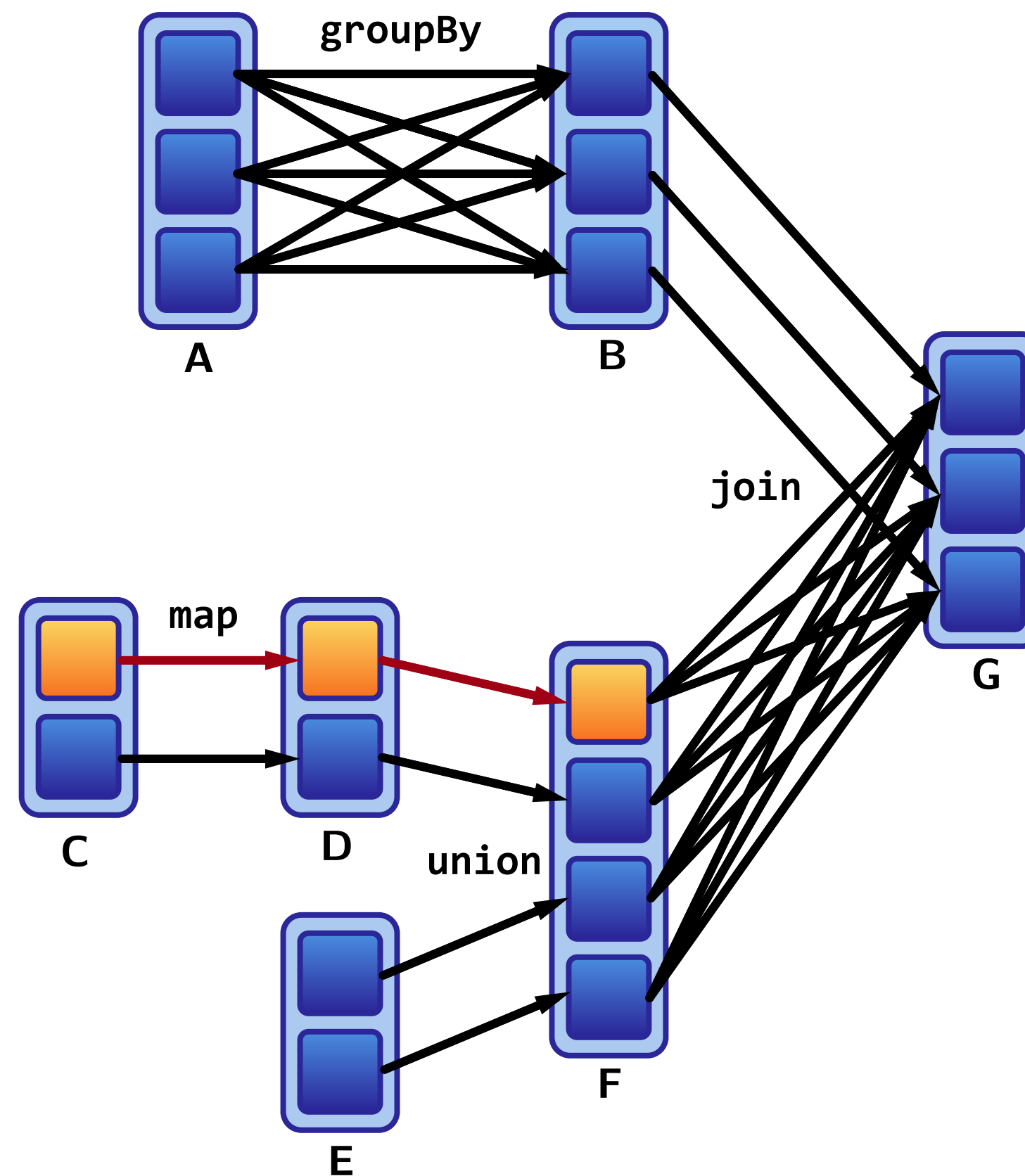**Lineages graphs are the key to fault tolerance in Spark.**

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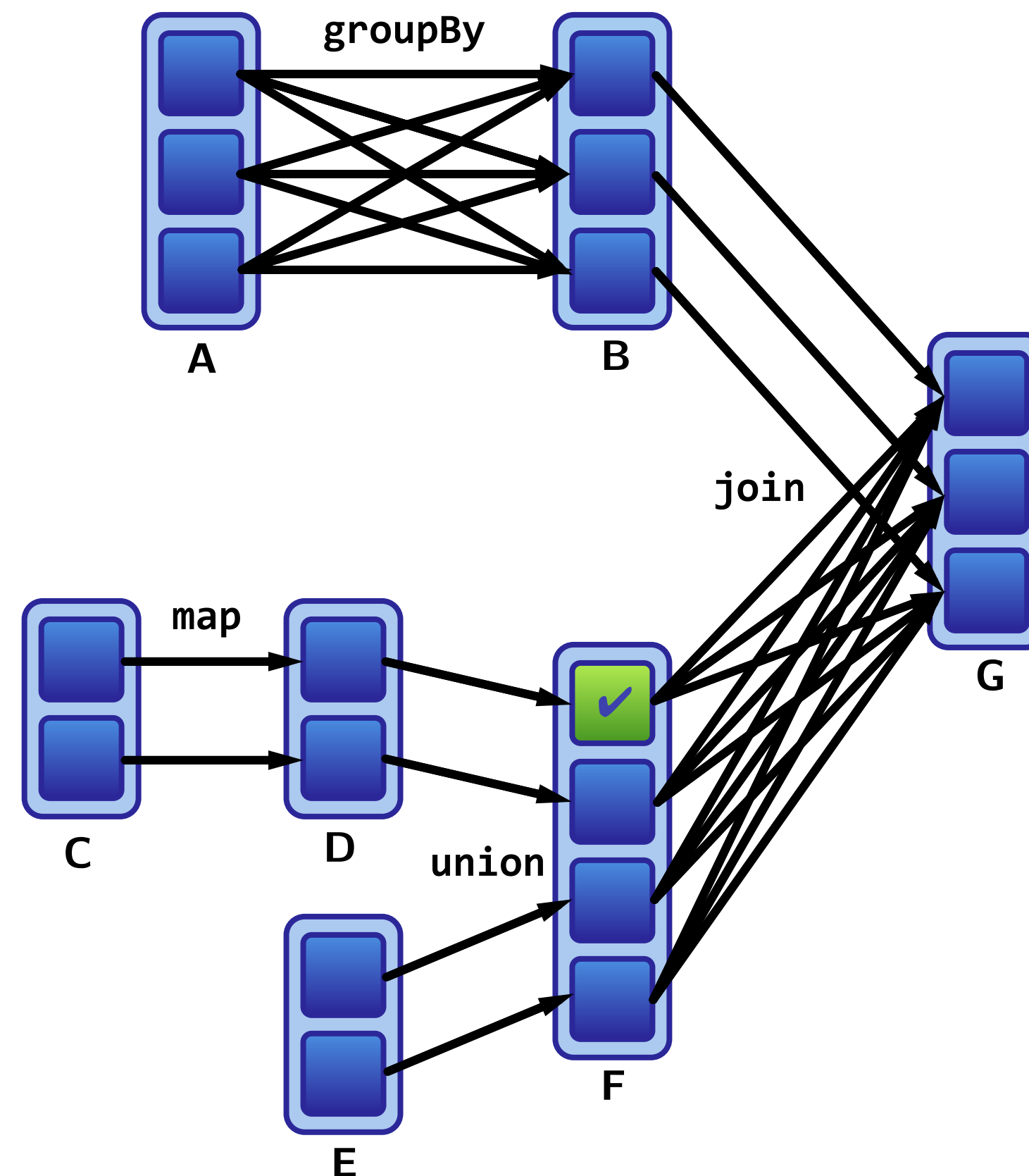
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Recomputing missing partitions fast for narrow dependencies. But slow for wide dependencies!

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