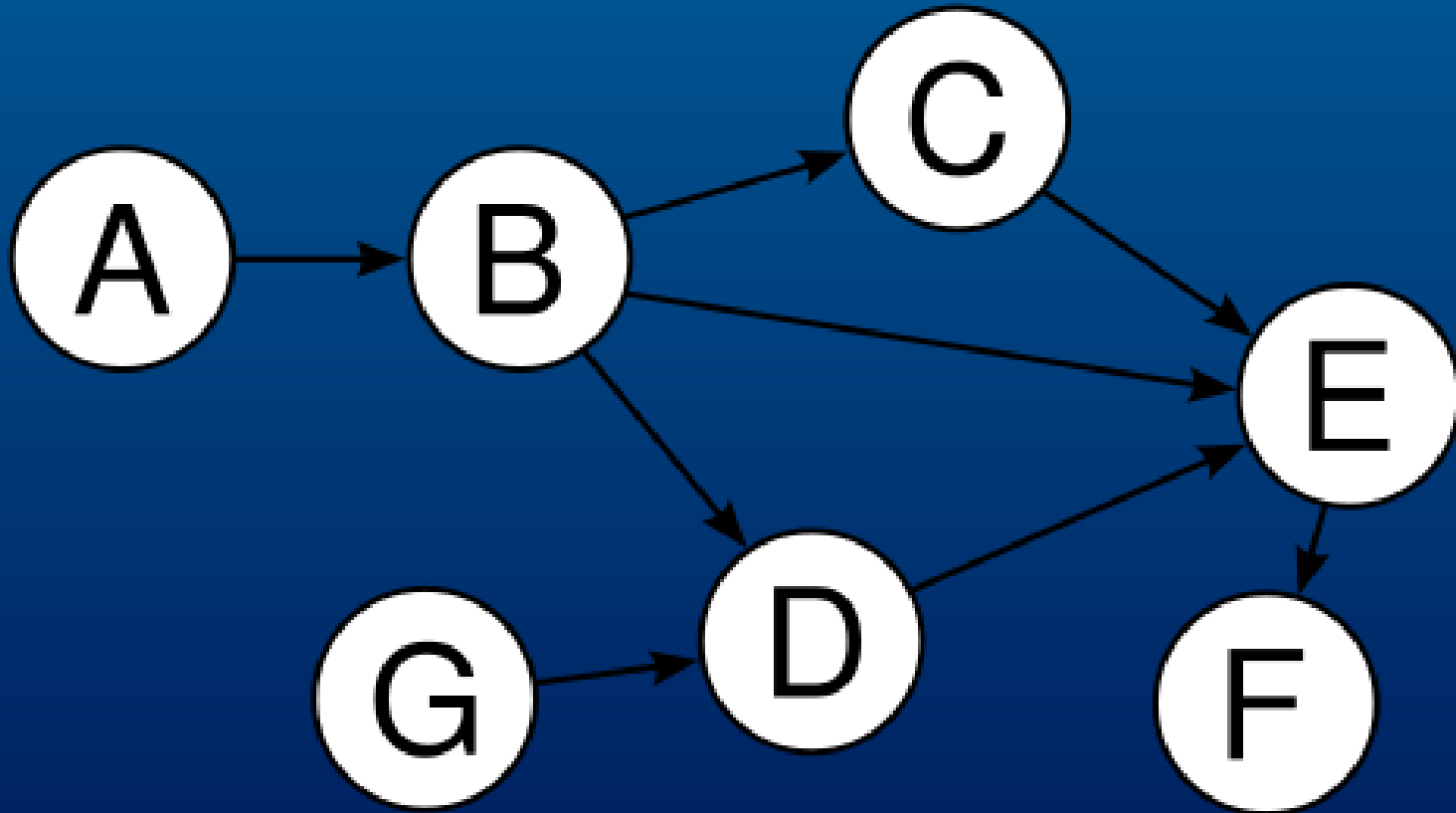


# Directed Acyclic Graph Scheduler

# Directed Acyclic Graphs



# Directed Acyclic Graphs

**Track dependencies!**  
(also known as lineage or  
provenance)

# DAG in Spark

- nodes are RDDs
- arrows are Transformations

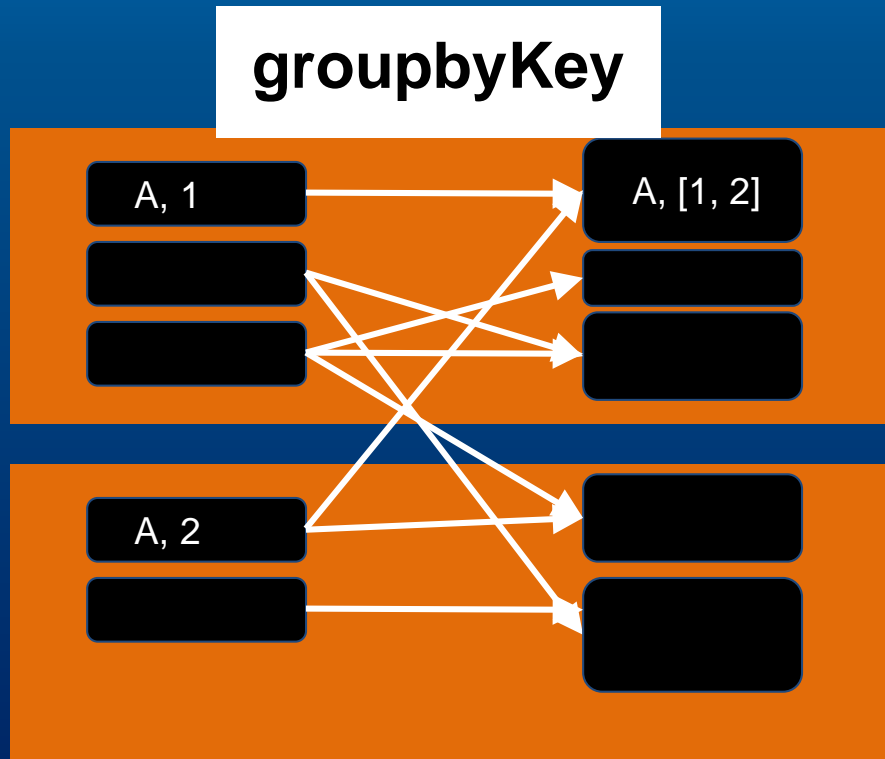
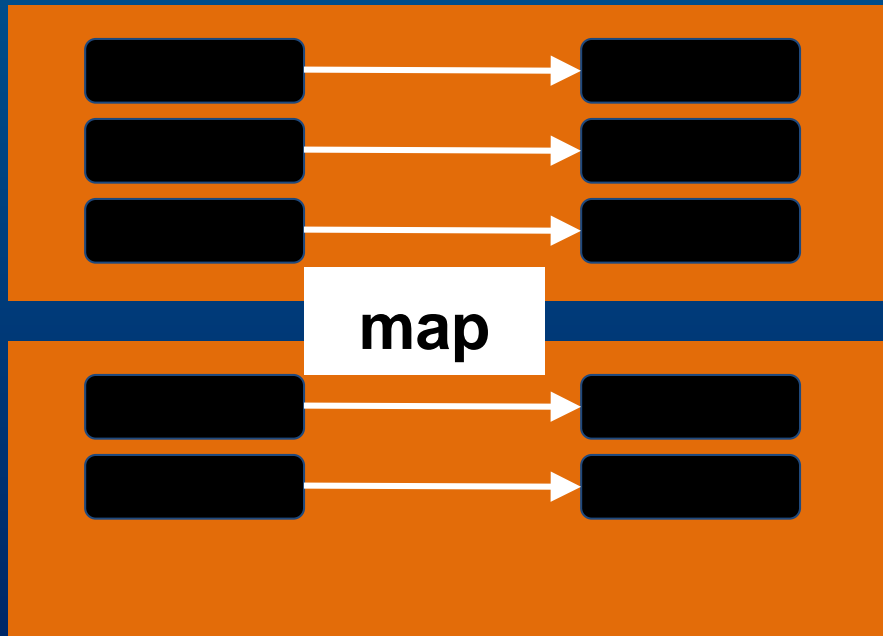
# Narrow

vs

# Wide

**map**

**groupByKey**



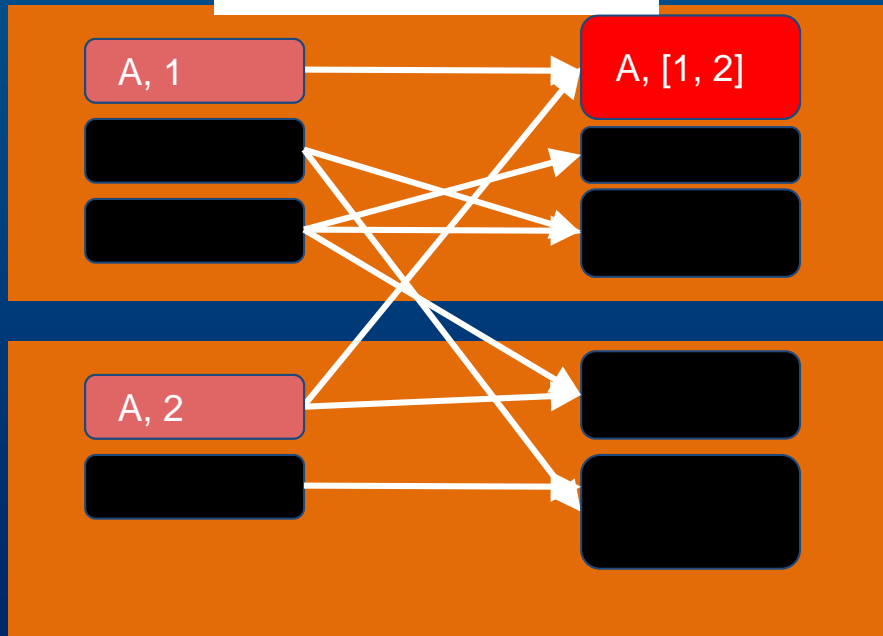
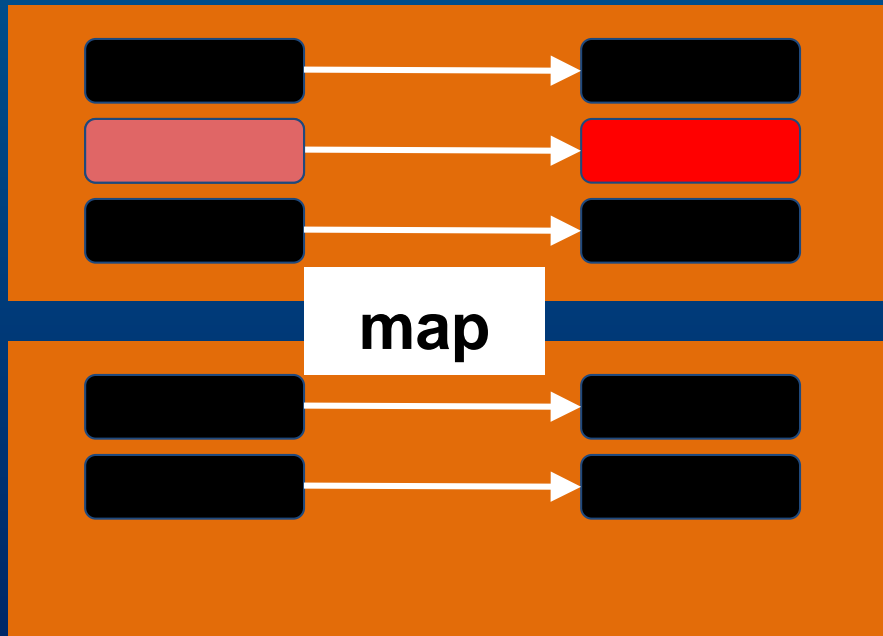
# Narrow

vs

# Wide

**map**

**groupByKey**



# Transformations of (K,V) pairs

```
def create_pair(word):  
    return (word, 1)
```

```
pairs_RDD = text_RDD.flatMap(split_words).map(create_pair)
```

```
for k,v in pairs_RDD.groupByKey().collect():
```

```
    print "Key:", k, ",Values:", list(v)
```

```
Out[]: Key: A , Values: [1]
```

```
Key: ago , Values: [1]
```

```
Key: far , Values: [1, 1]
```

```
Key: away , Values: [1]
```

```
Key: in , Values: [1]
```

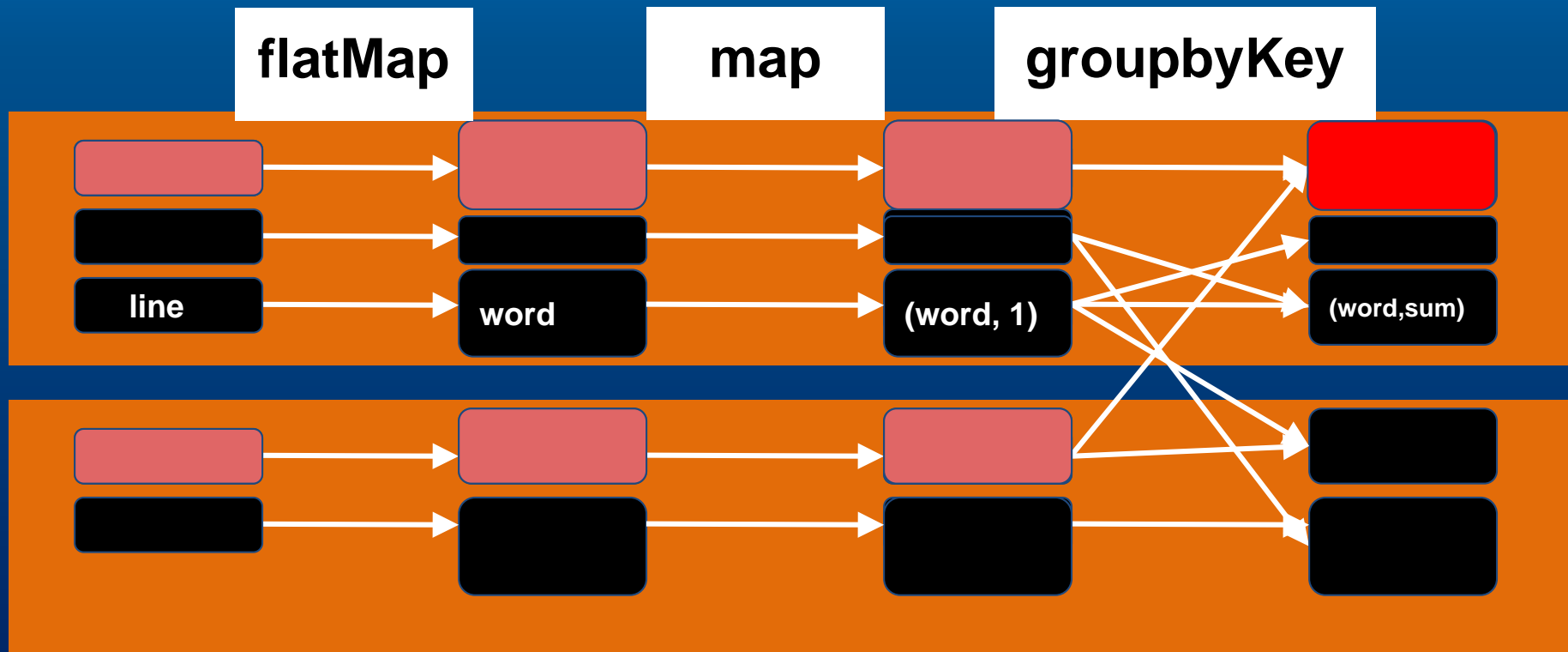
```
Key: long , Values: [1]
```

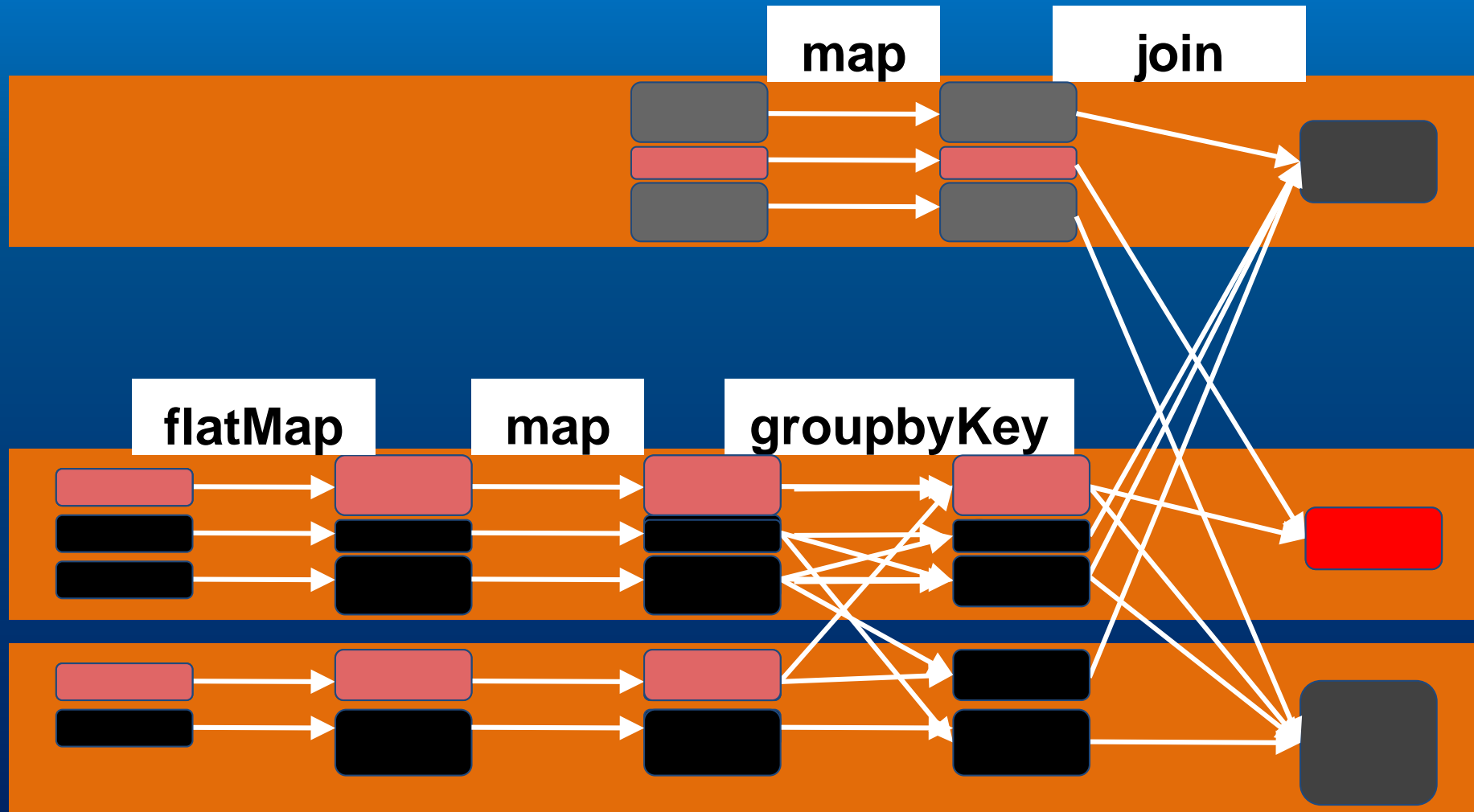
```
Key: a , Values: [1]
```

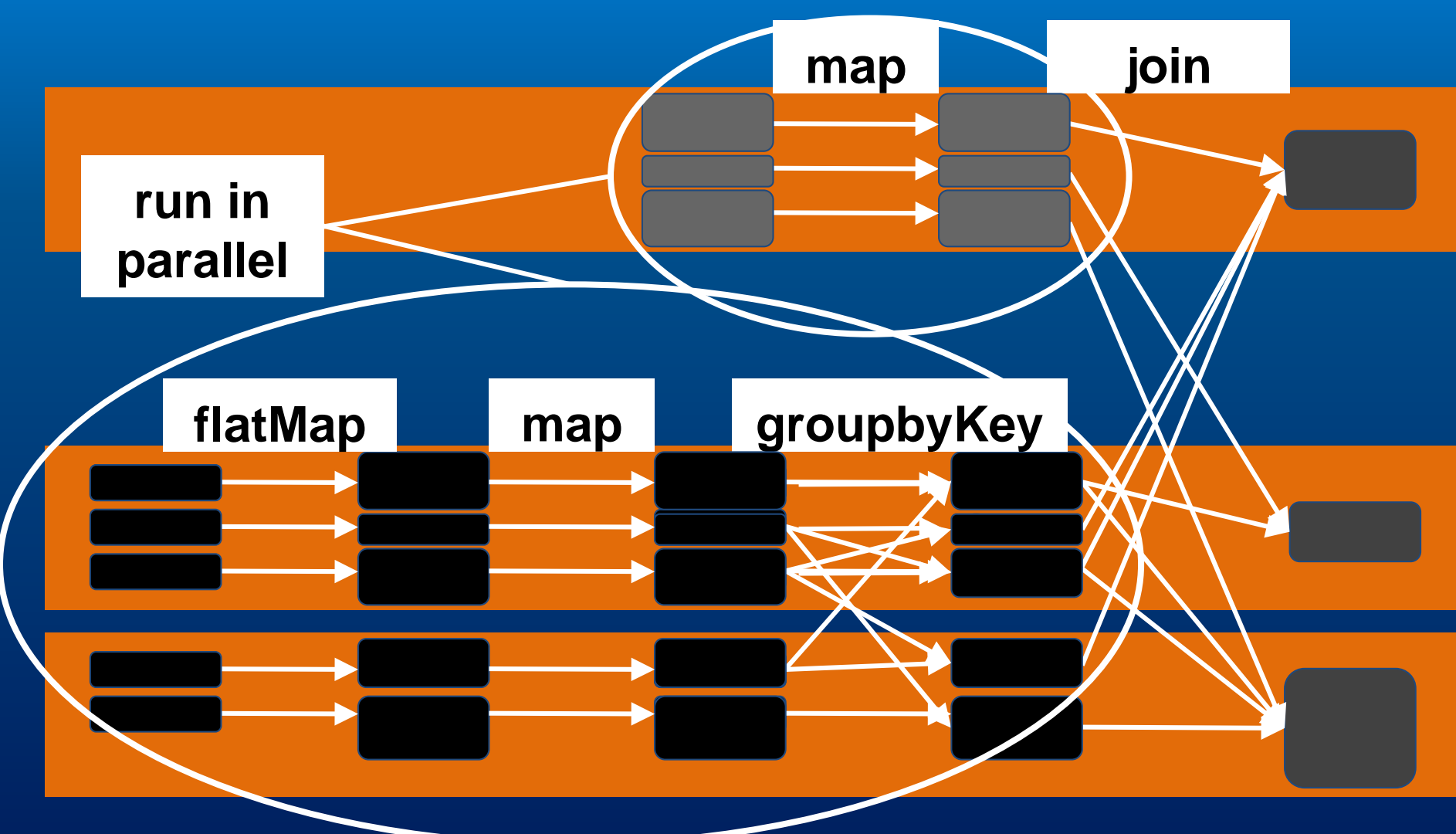
```
<MORE output>
```



# Spark DAG of transformations







Actions

# What is an action

- Final stage of workflow
- Triggers execution of the DAG
- Returns results to the Driver or writes to HDFS

# Driver Program

Spark  
Context

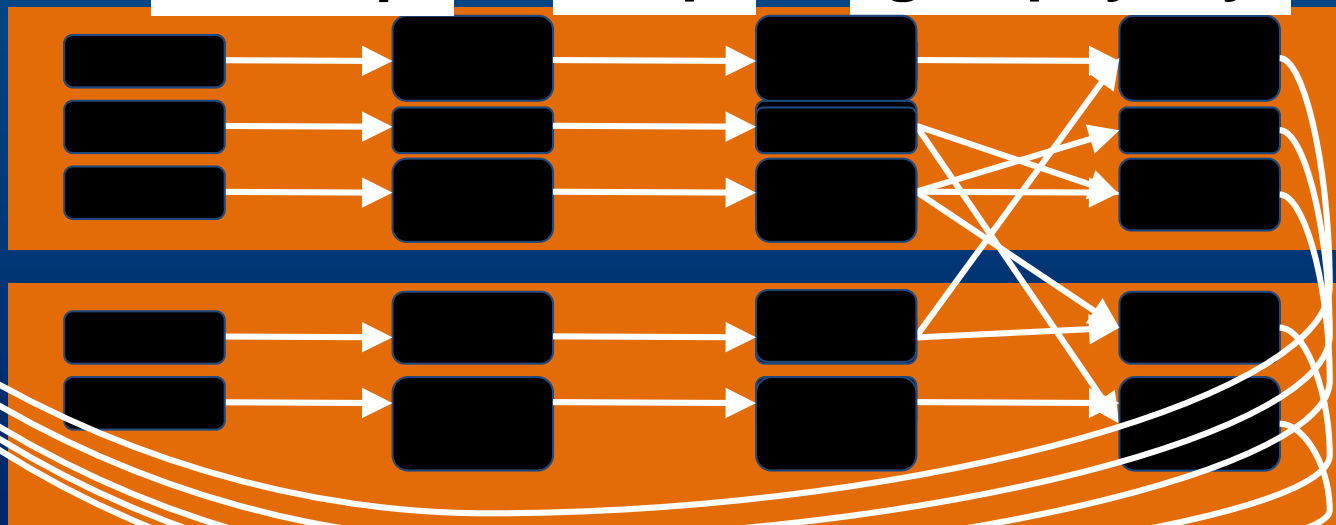
  
Spark  
Context

flatMap

map

groupByKey

collect



# Actions

- `collect()` - copy all elements to the driver
- `take(n)` - copy first n elements
- `reduce(func)` - aggregate elements with func  
(takes 2 elements, returns 1)
- `saveAsTextFile(filename)` - save to local file or HDFS

# Caching



# Caching

- By default each job re-processes from HDFS
- Mark RDD with `.cache()`
- Lazy

# When?

- Generally not the input data
- Do validation and cleaning
- Cache for iterative algorithm

# How?

- Memory (most common)
- Disk (rare)
- Both (for heavy calculations)

# Speedup

- Easily 10x or even 100x depending on application
- Caching is gradual
- Fault tolerant

# Wordcount with caching

from HDFS:

```
text_RDD =
```

```
sc.textFile("/user/cloudera/input/testfile1")
```

```
def split_words(line):
```

```
    return line.split()
```

```
|
```

```
def create_pair(word):
```

```
    return (word, 1)
```

```
|
```

```
pairs_RDD=text_RDD.flatMap(split_words).map(create_pair)
```

```
pairs_RDD.cache()
```

```
def sum_counts(a, b):
```

```
    return a + b
```

```
wordcounts_RDD = pairs_RDD.reduceByKey(sum_counts)
```

First job:

```
wordcounts_RDD.collect()
```

Second job:

```
pairs_RDD.take(1)
```

# Broadcast variables



# Broadcast variables

- Large variable used in all nodes
- Transfer just once per Executor
- Efficient peer-to-peer transfer

# Broadcast variable example

For example large configuration dictionary  
or lookup table:

```
config = sc.broadcast({"order":3, "filter":True})
```

```
config.value
```

# Accumulators

# Accumulator

- Common pattern of accumulating to a variable across the cluster
- Write-only on nodes

# Accumulator example

```
accum = sc.accumulator(0)
```

```
def test_accum(x):
```

```
    accum.add(x)
```

```
sc.parallelize([1, 2, 3, 4]).foreach(test_accum)
```

```
accum.value
```

```
Out[]: 10
```