



# CS61A Lecture 41

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UC Berkeley  
April 26, 2013

# Announcements



- HW13 due Wednesday
- Scheme project due Monday
- Scheme contest deadline extended to Friday

# CPU Performance



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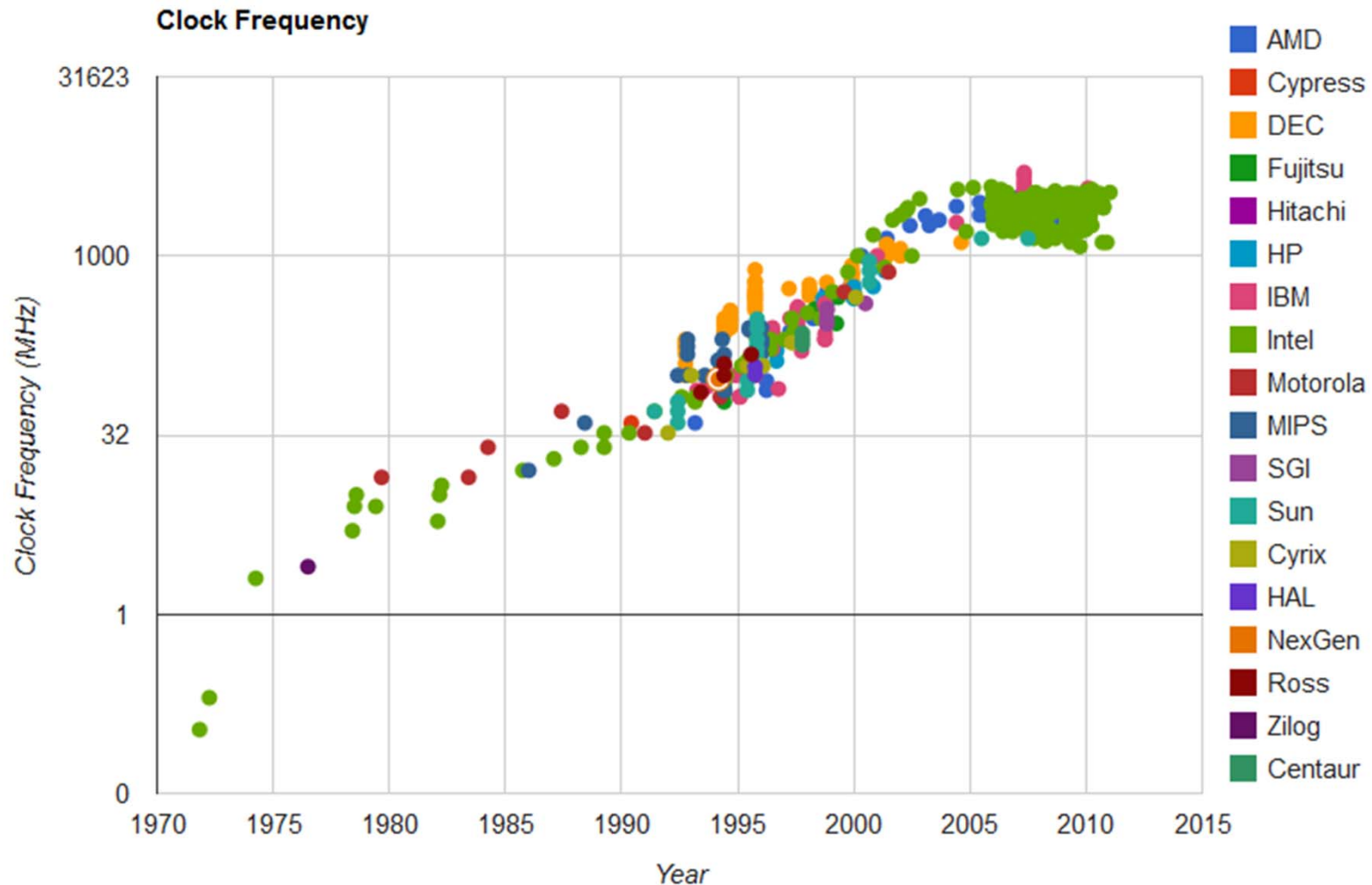
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<http://cpudb.stanford.edu>

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Next time: the hard case, where shared data is required



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- Pure functions enable an abstraction barrier between data processing logic and distributed system administration

# Systems



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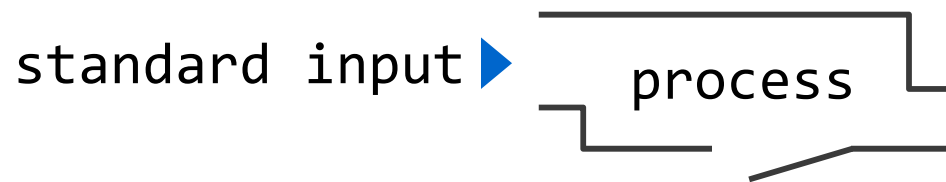


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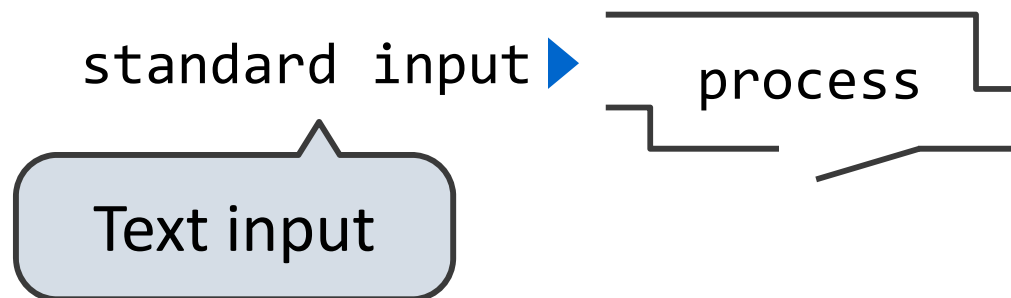


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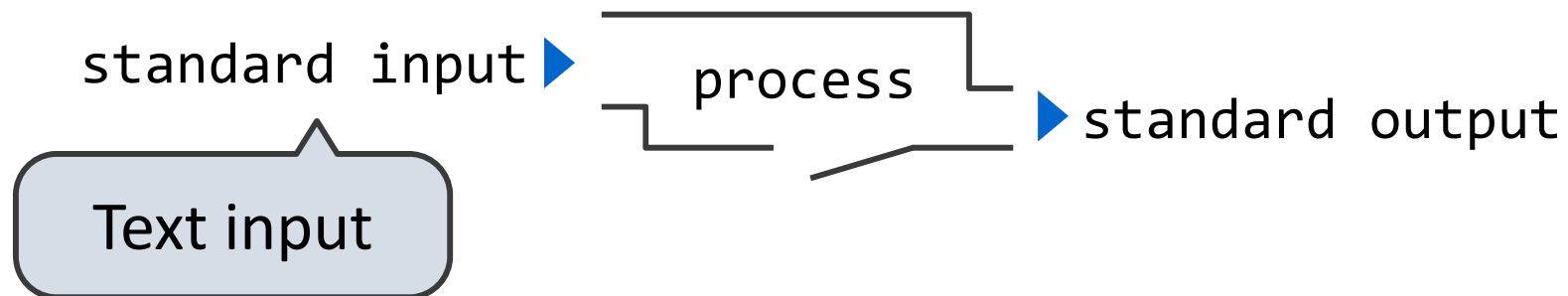


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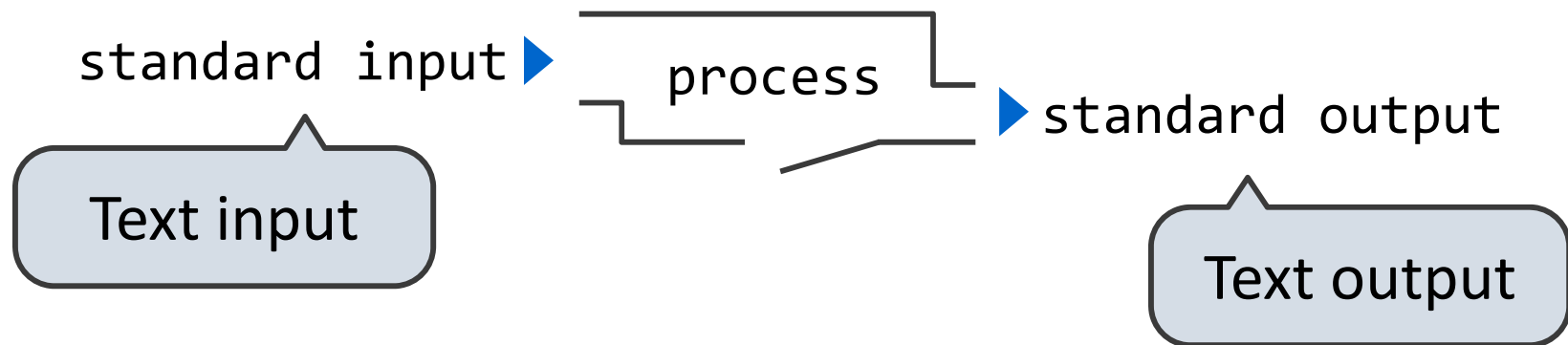


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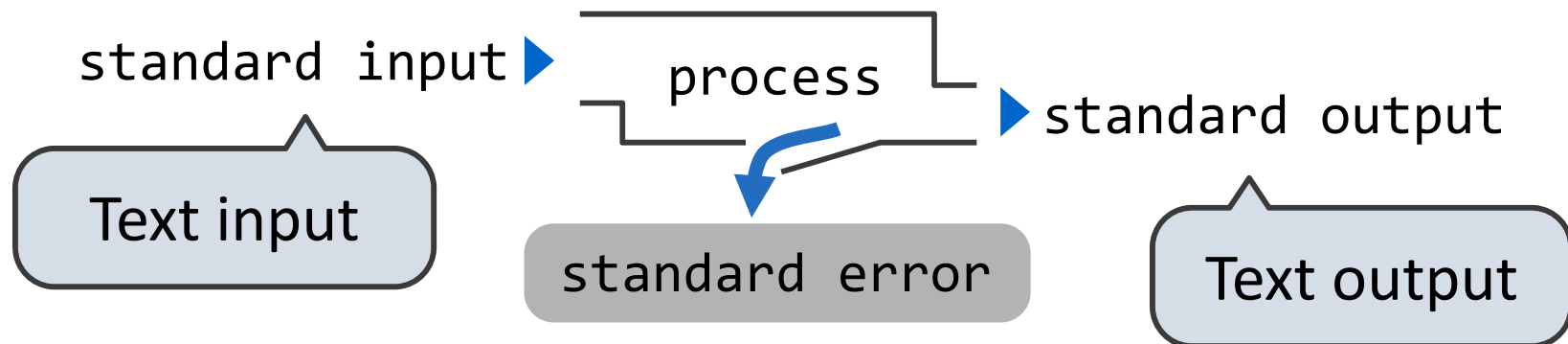


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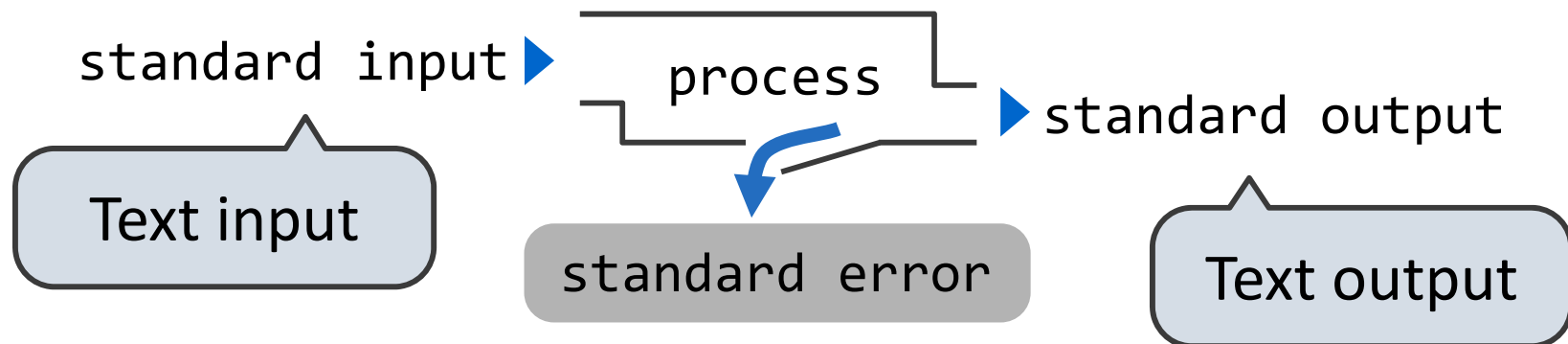


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The *standard streams* in a Unix-like operating system are conceptually similar to Python iterators

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Using these "files" takes advantage of the operating system *standard stream* abstraction

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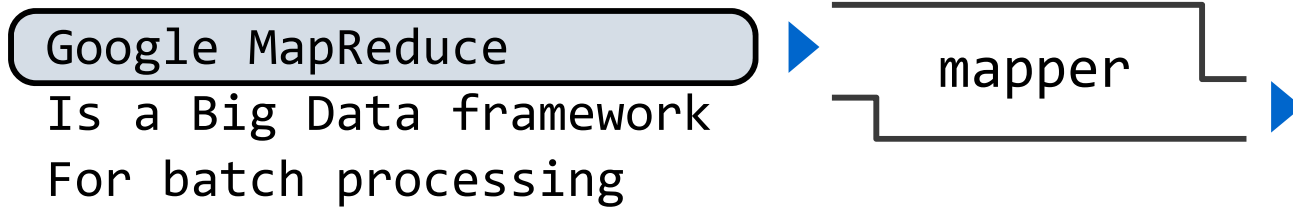


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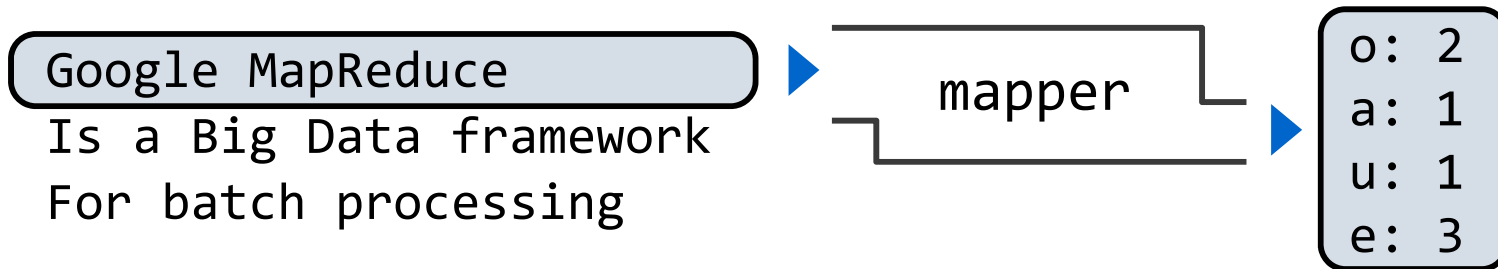


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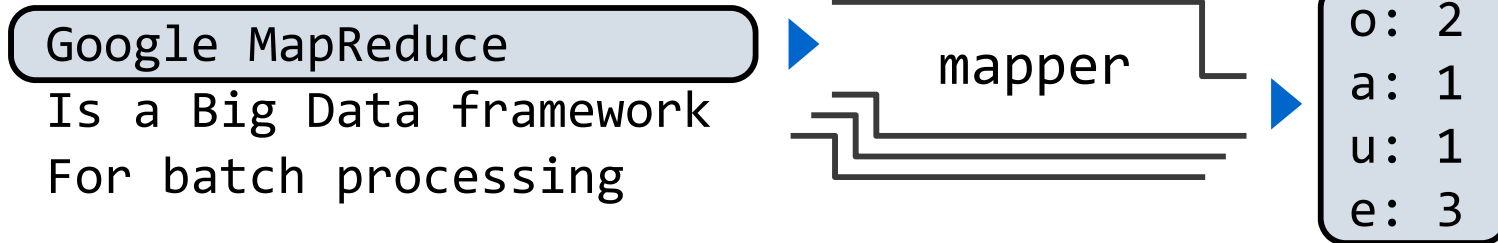


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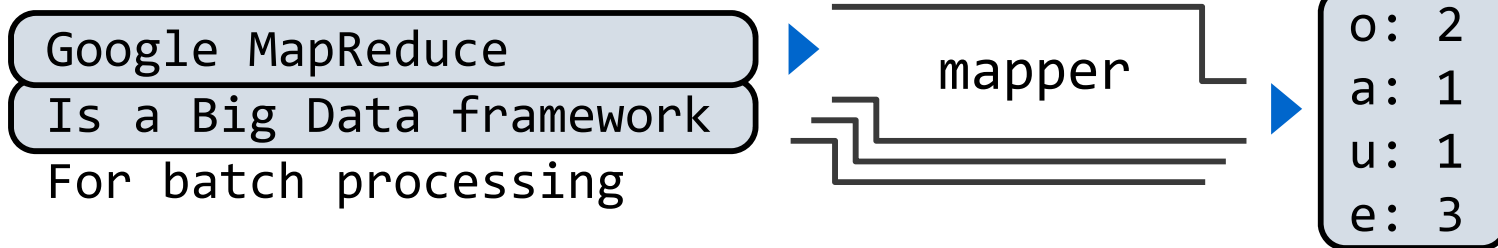


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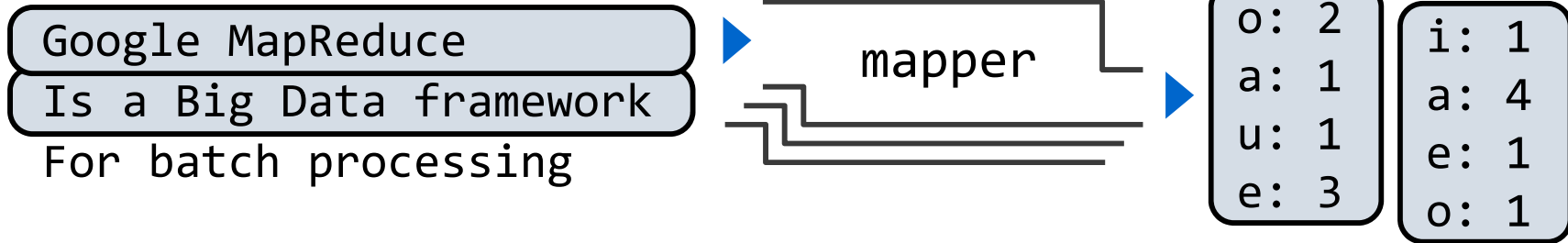


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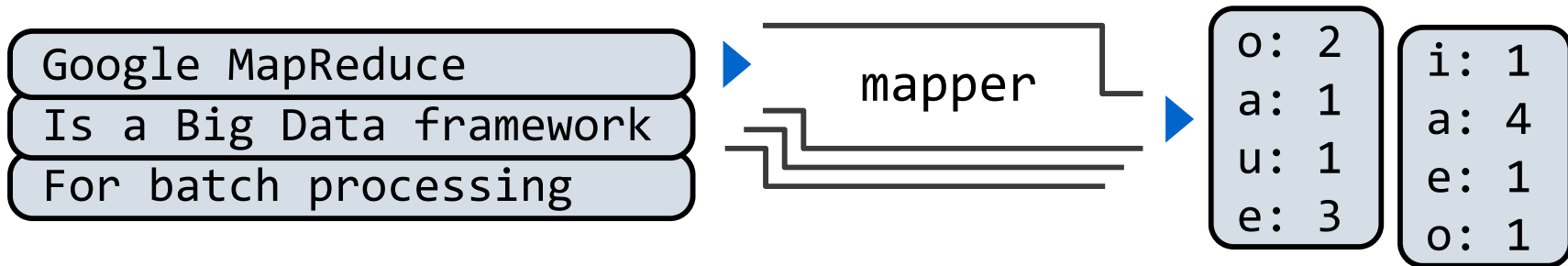


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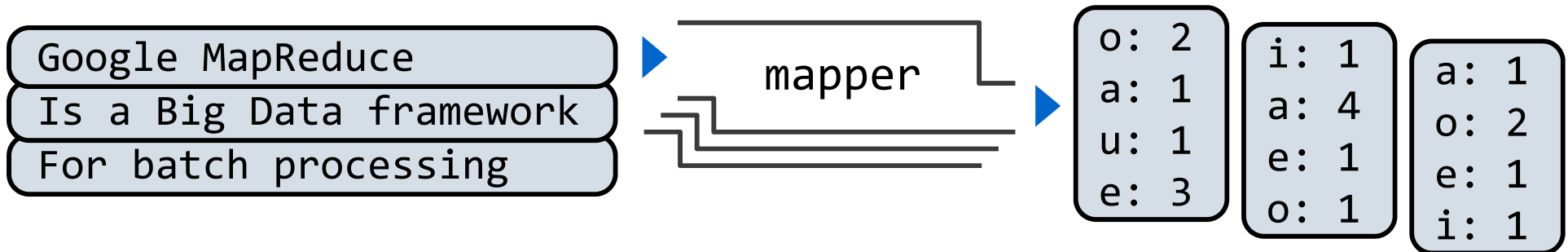


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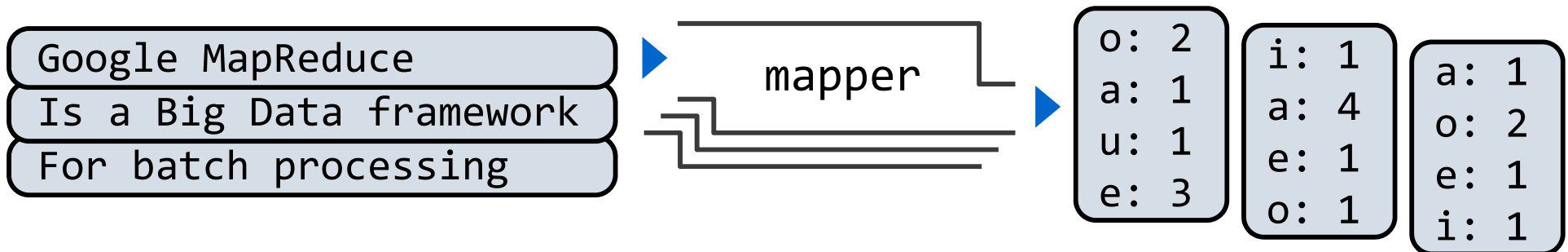


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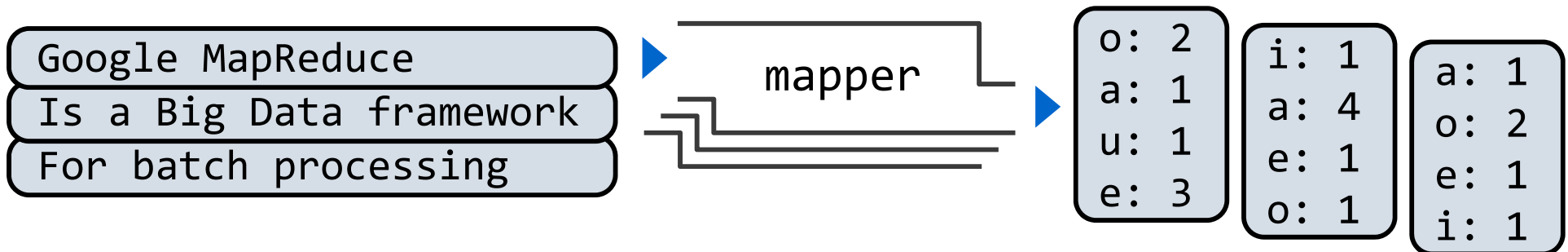
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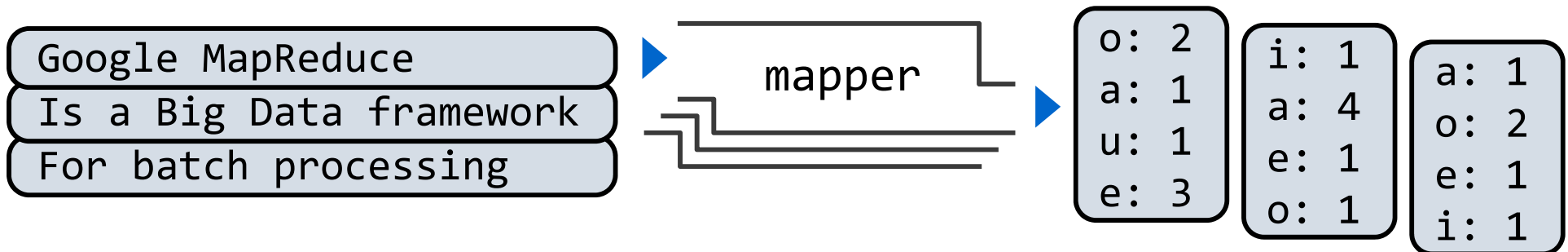
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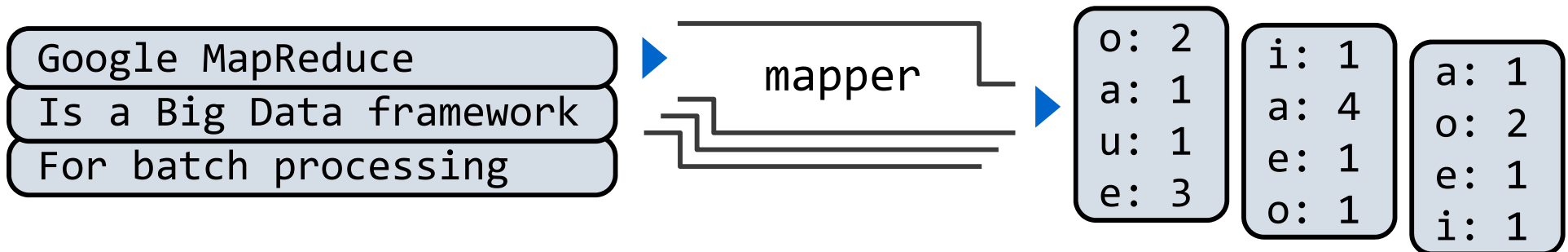
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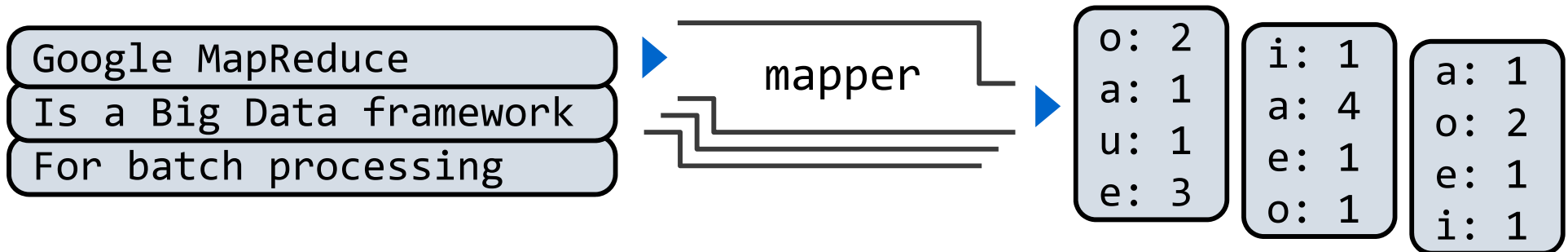
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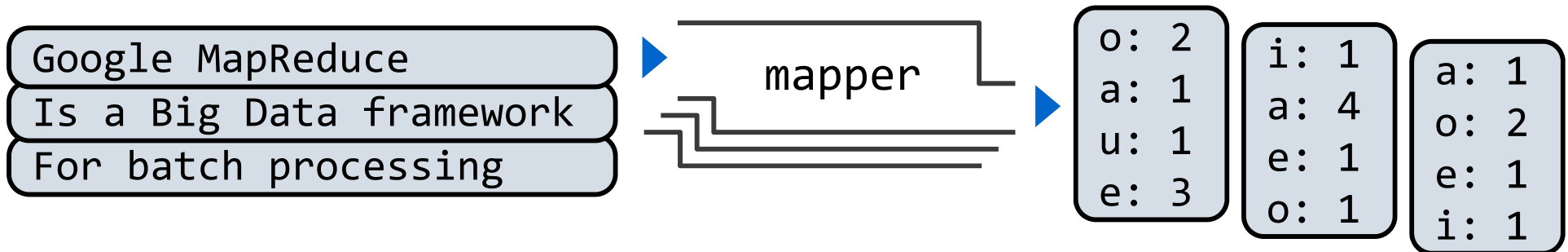


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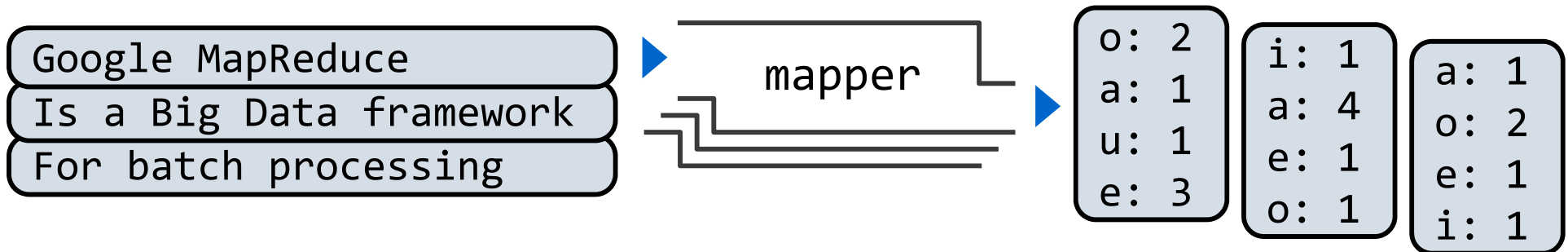


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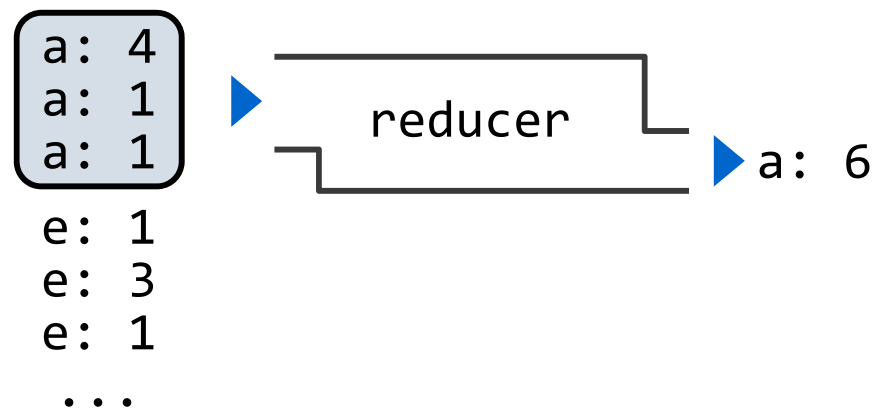
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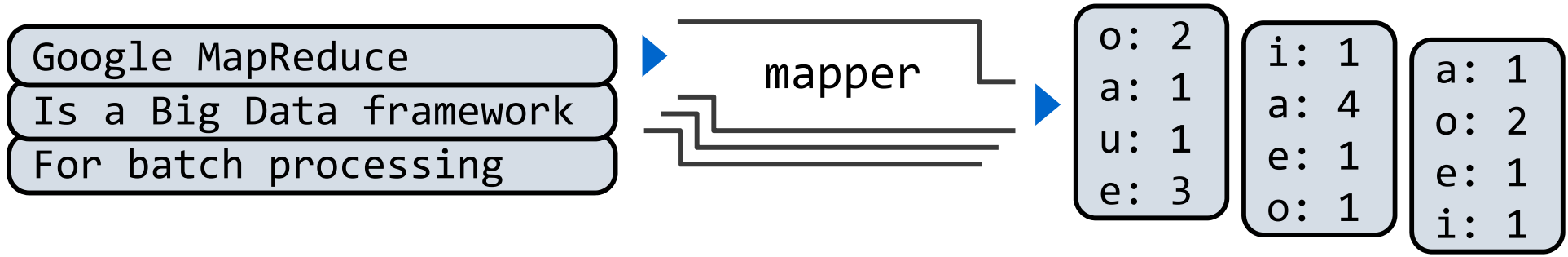


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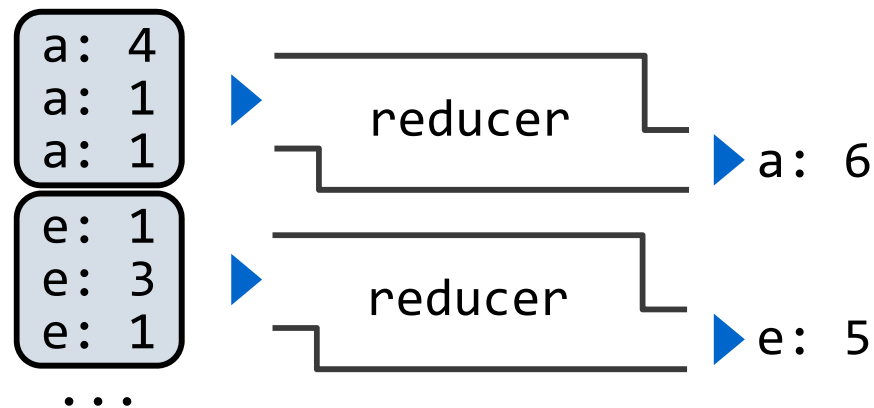


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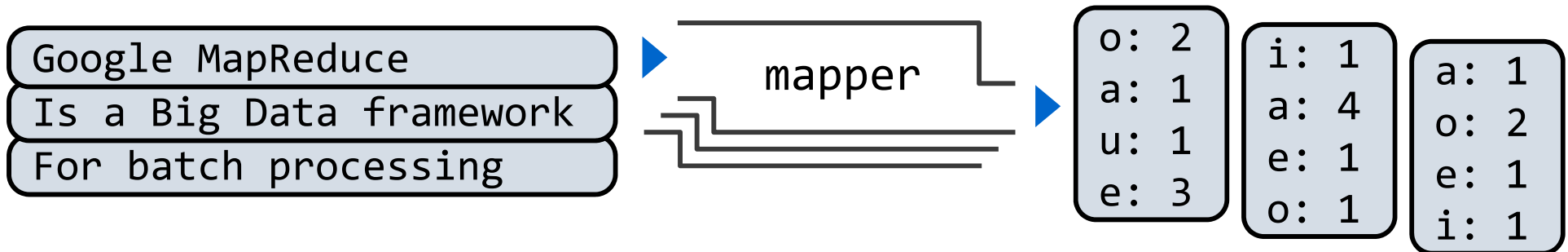


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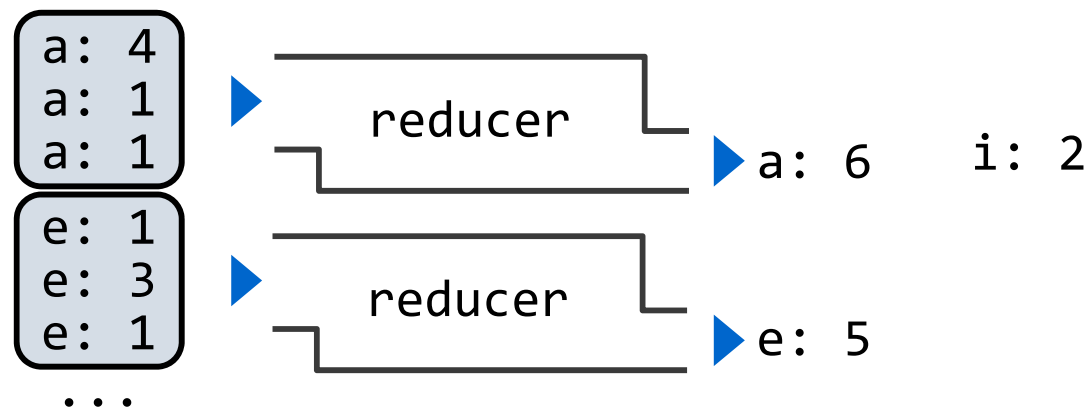


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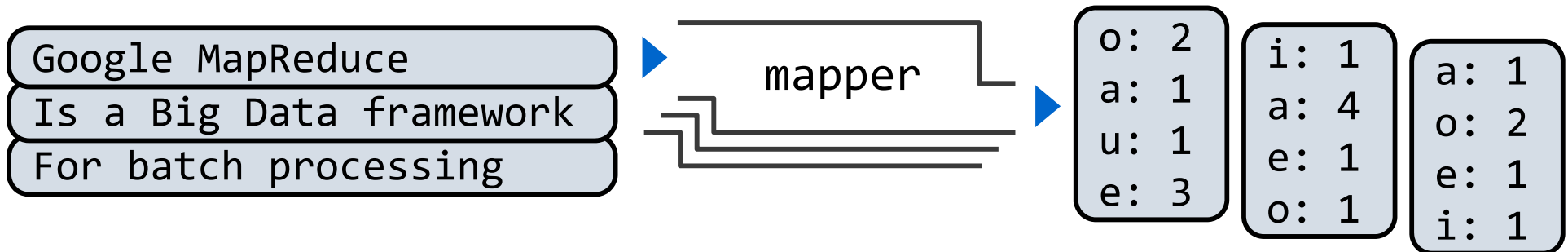


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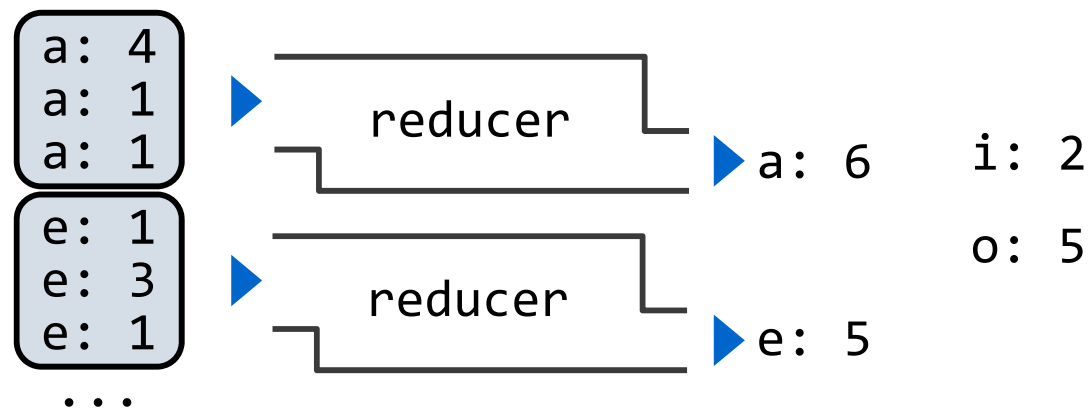


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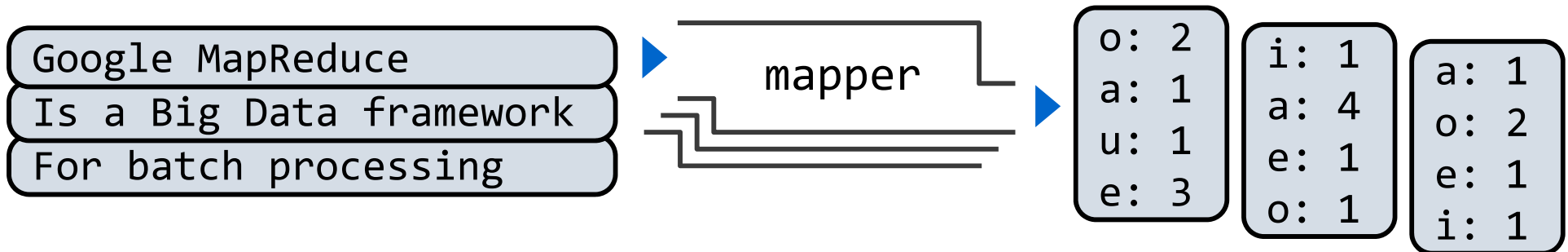


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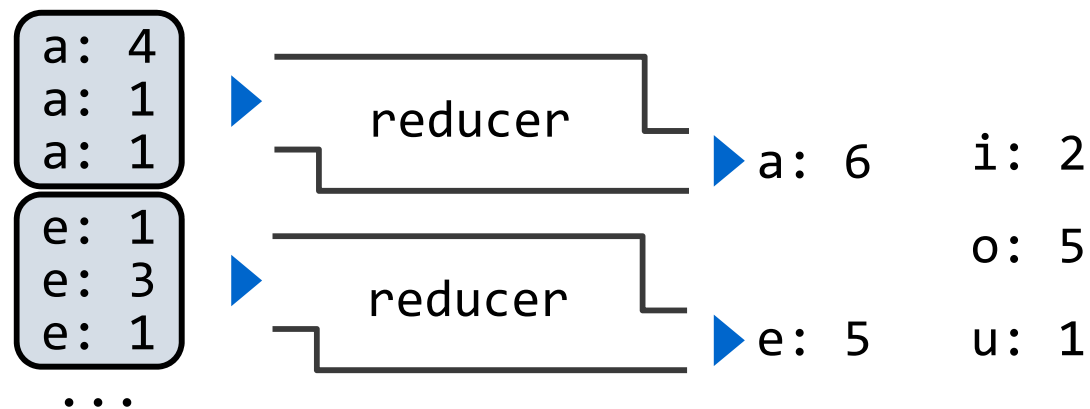


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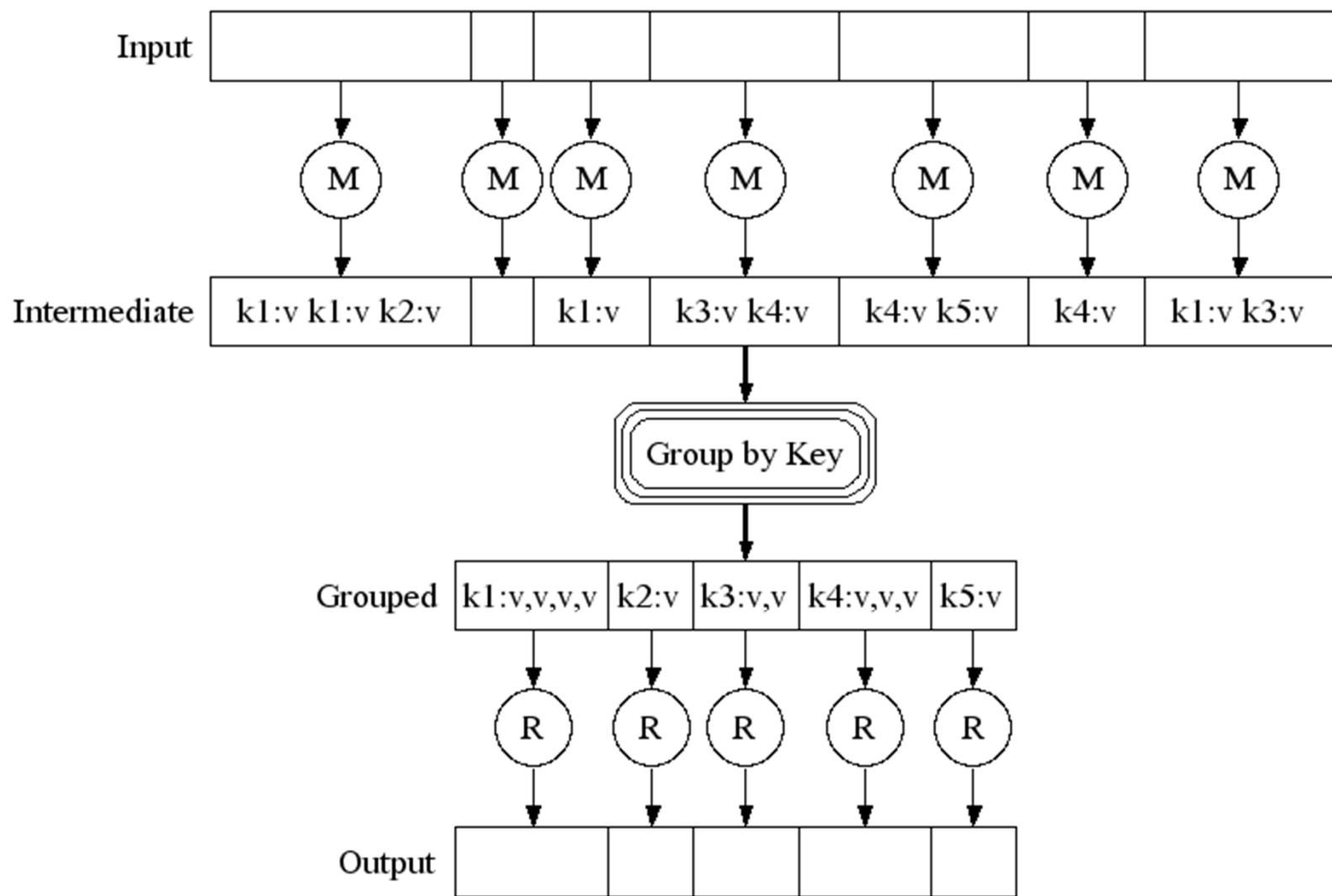


**Reduce phase:** For each **intermediate key**, apply a *reducer* function to accumulate all values associated with that key

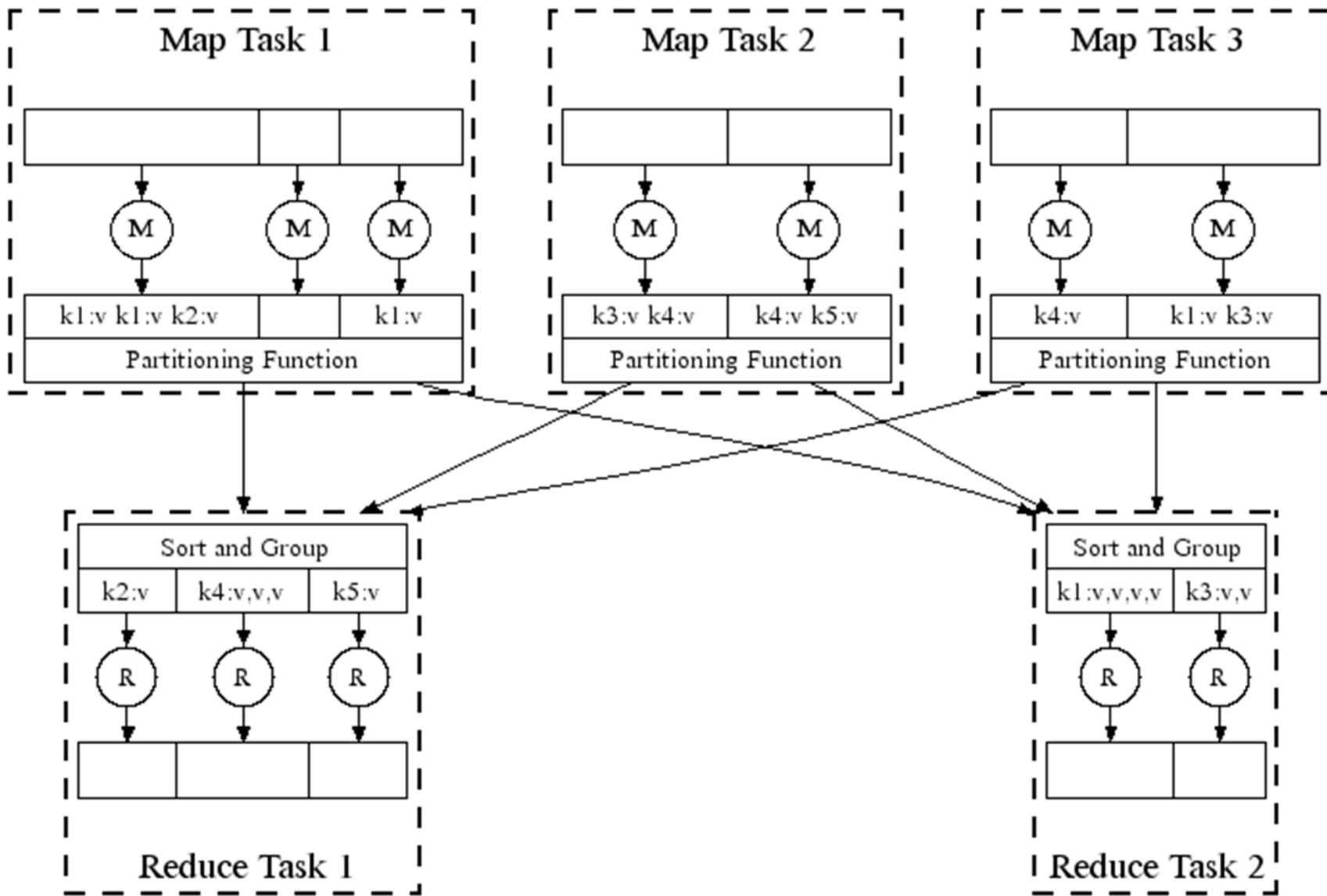
- The *reducer* takes an iterator over **key-value pairs**
- All pairs with a given key are consecutive
- The *reducer* yields 0 or more values, each associated with that **intermediate key**



# Above-the-Line: Execution Model

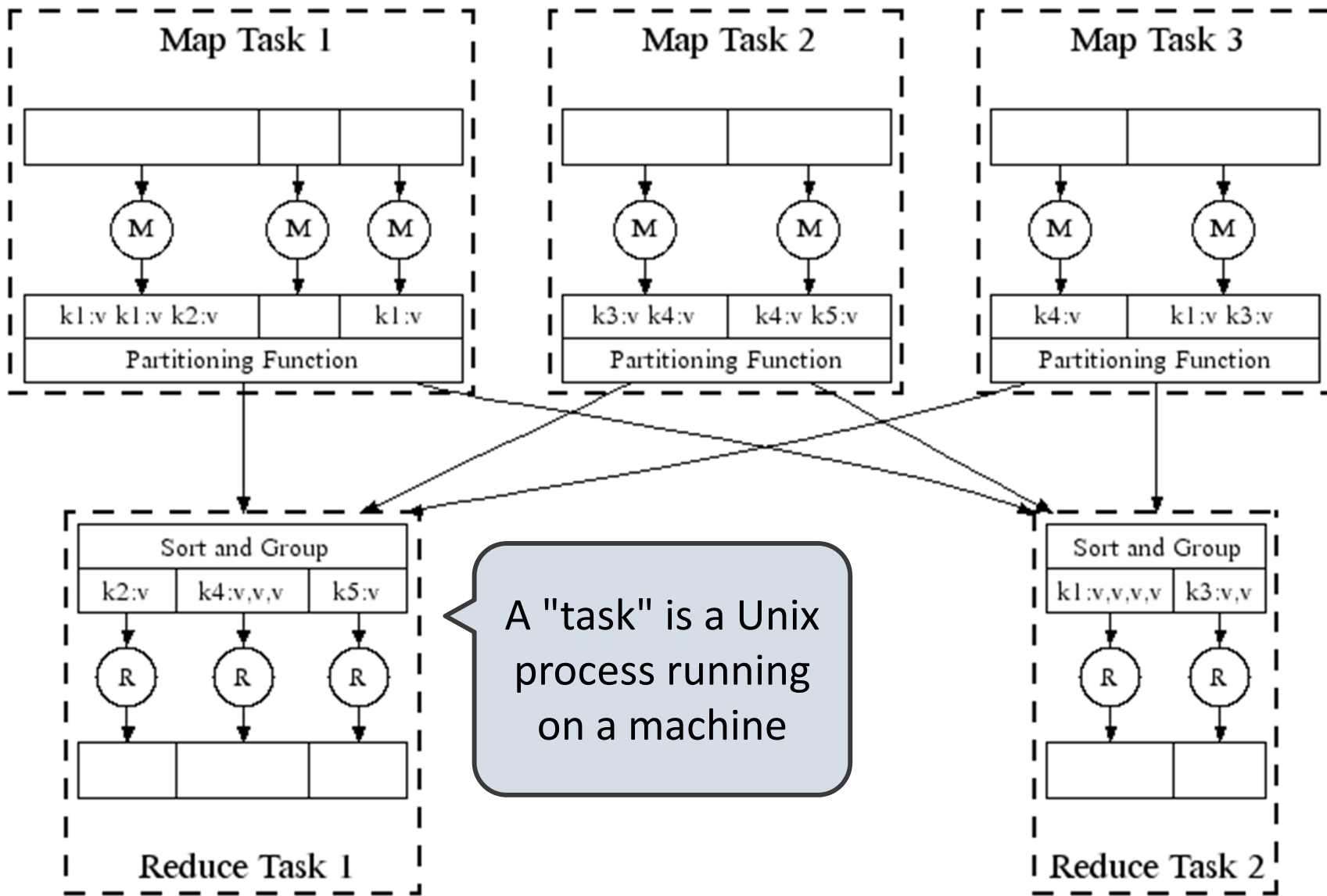


# Below-the-Line: Parallel Execution

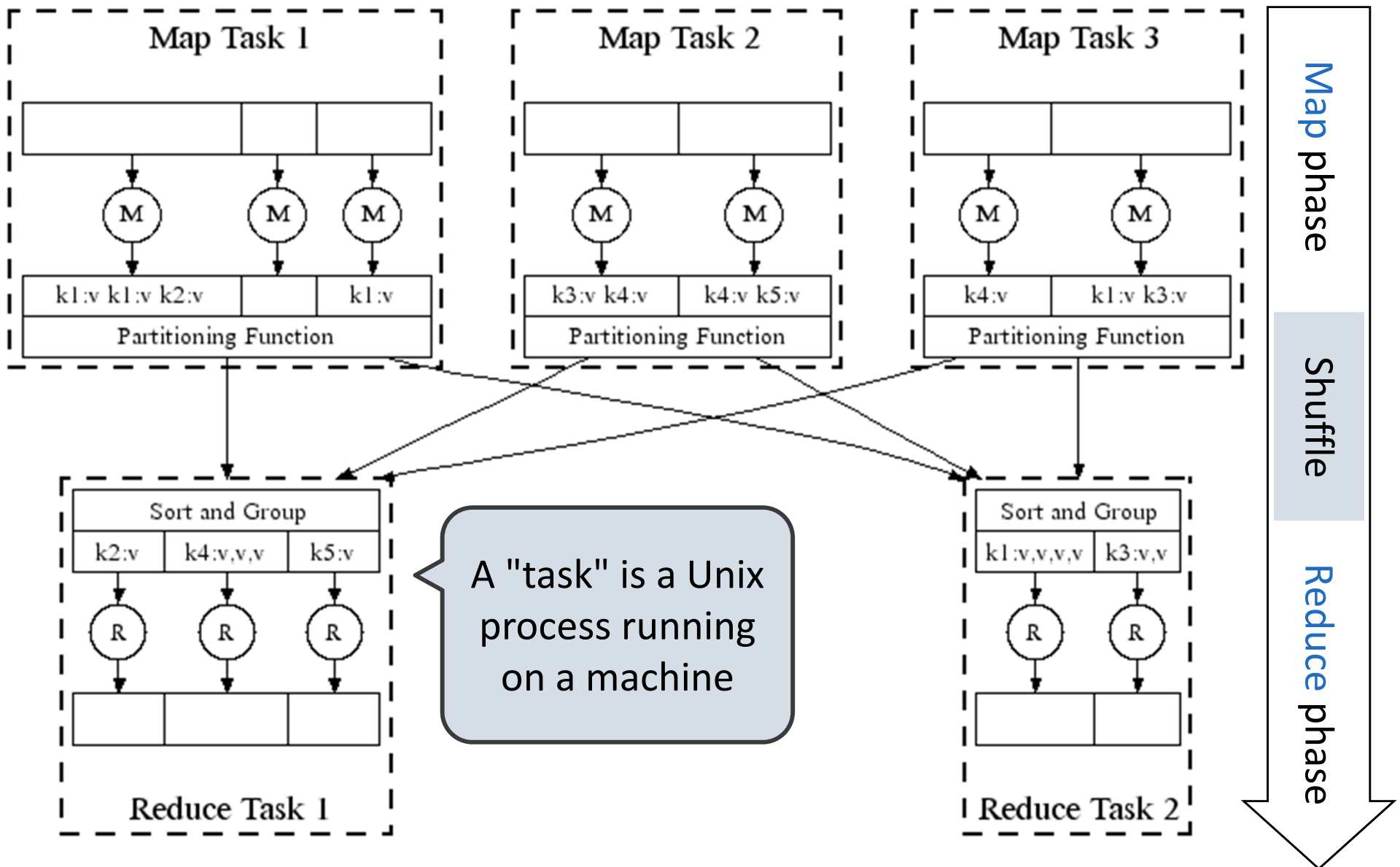




# Below-the-Line: Parallel Execution



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# MapReduce Assumptions



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In MapReduce, these functional programming ideas allow:

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- Re-computation and caching of results, as needed

# Python Example of a MapReduce Application

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## Mapper



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def emit_vowels(line):  
    for vowel in 'aeiou':  
        count = line.count(vowel)  
        if count > 0:  
            emit(vowel, count)
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for line in sys.stdin:
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Mapper inputs are lines of text provided to standard input

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**Reducer**

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A light blue rounded rectangular callout box with a black border and a small tail pointing towards the code line for `group_values_by_key`.

Takes and returns iterators

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for key, value_iterator in group_values_by_key(sys.stdin):  
    emit(key, sum(value_iterator))
```

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**Monitoring:** Will my job finish before dinner?!?

- The framework provides a web-based interface describing jobs