61A Lecture 36

Monday, December 1

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- Final exam held on Thursday 12/18 3pm-6pm (review info later this week)

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Hide complexity, but retain flexibility

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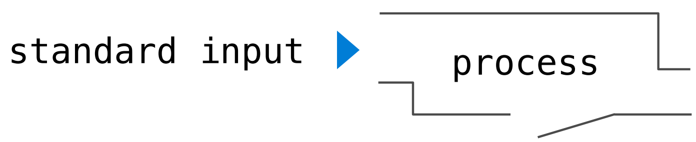

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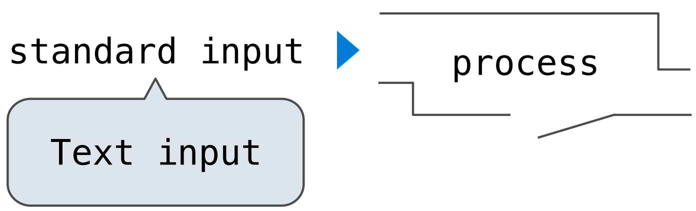

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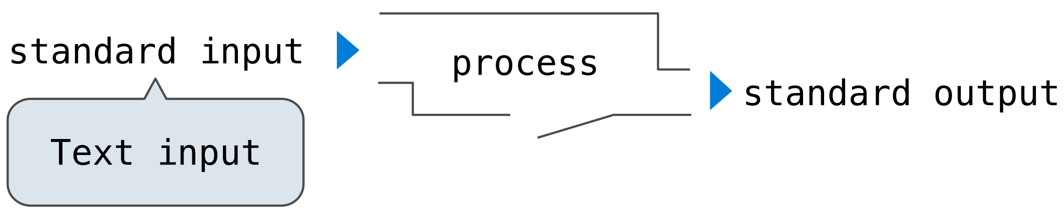

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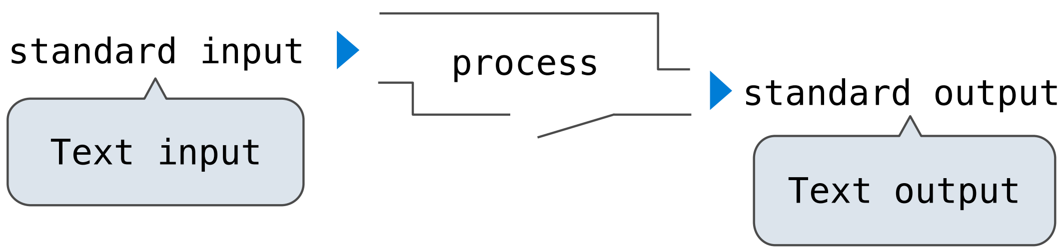

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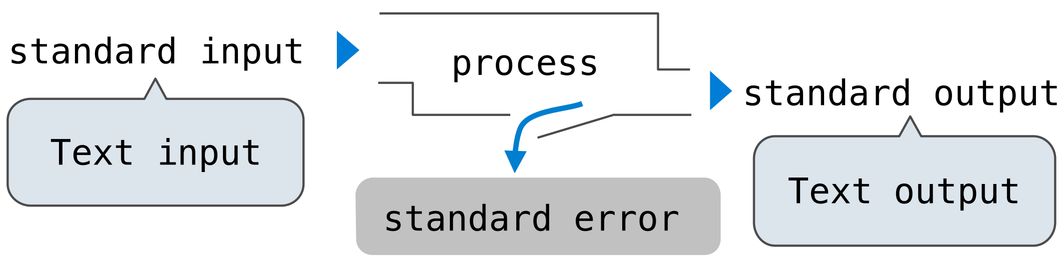

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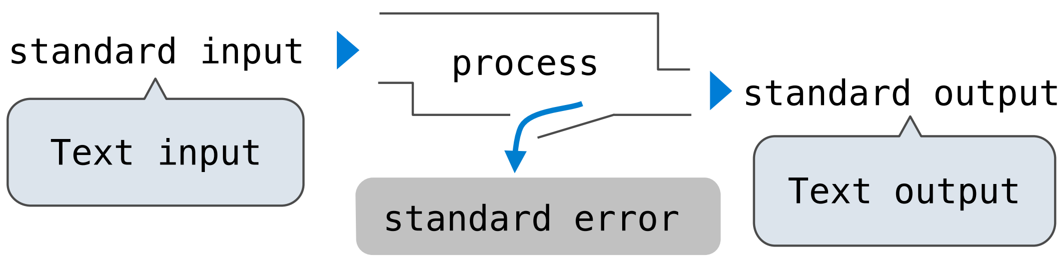

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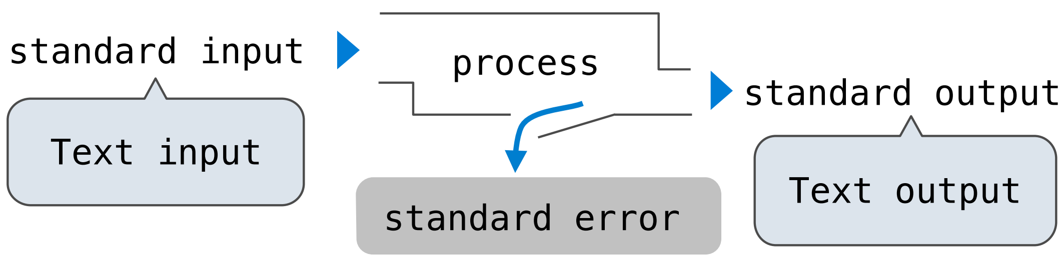

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(Demo)

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ls hw* | grep -v html | cut -f 1 -d '.' | cut -c 3- | sort -n
```

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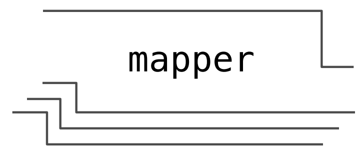


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a: 1
u: 1
e: 3
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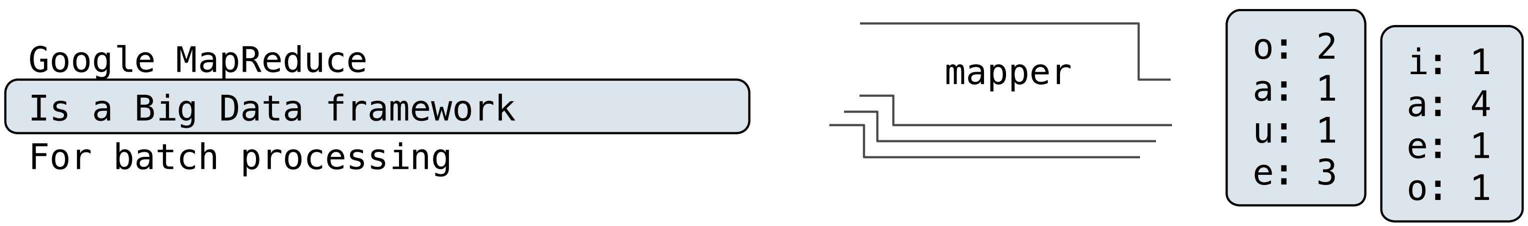

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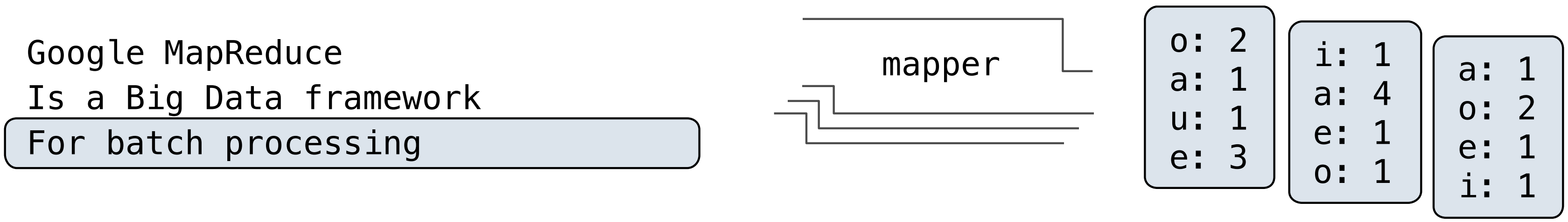

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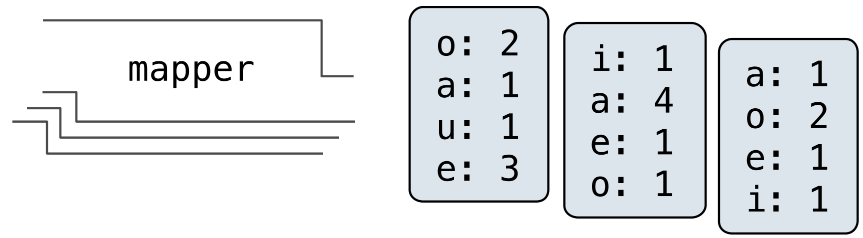

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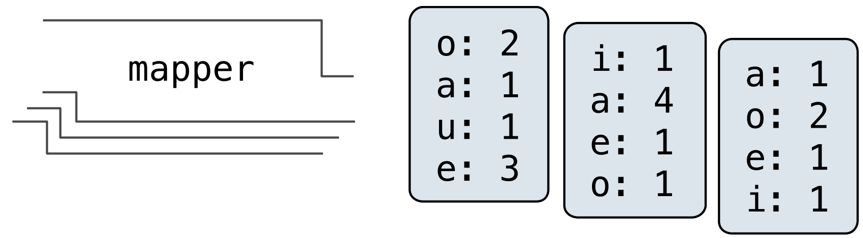

Reduce phase: For each intermediate key, apply a *reducer* function to accumulate all values associated with that key

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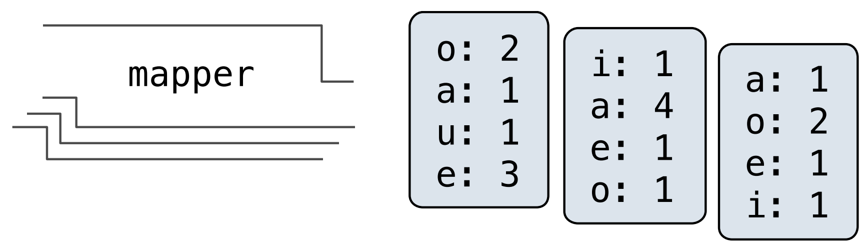

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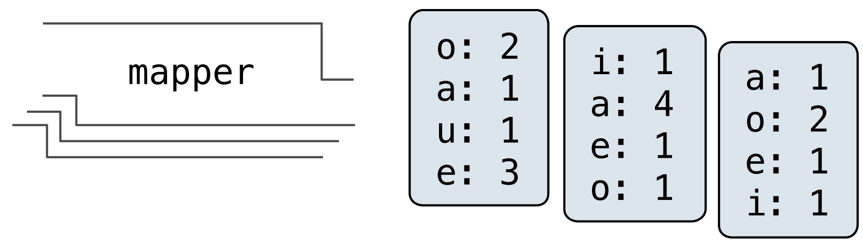

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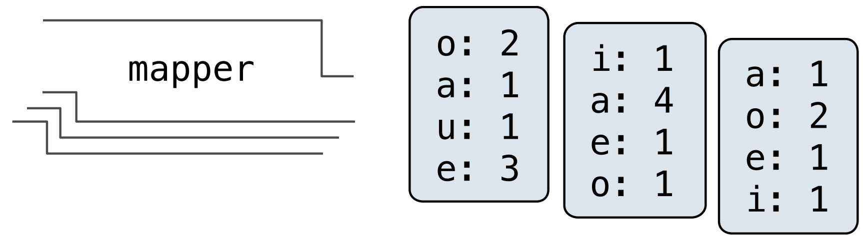

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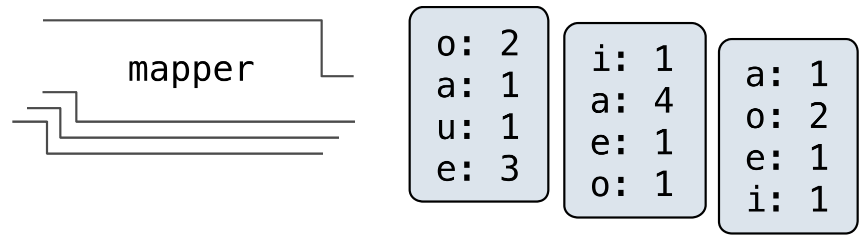

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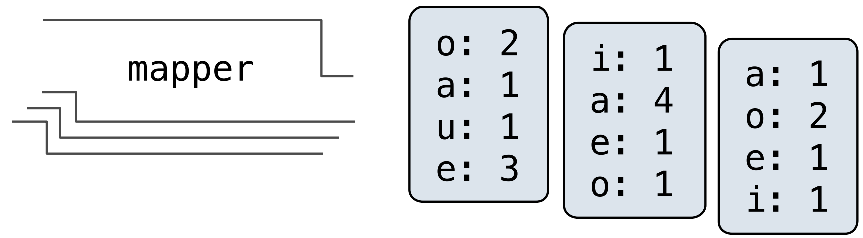

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```
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e: 1
e: 3
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...
```

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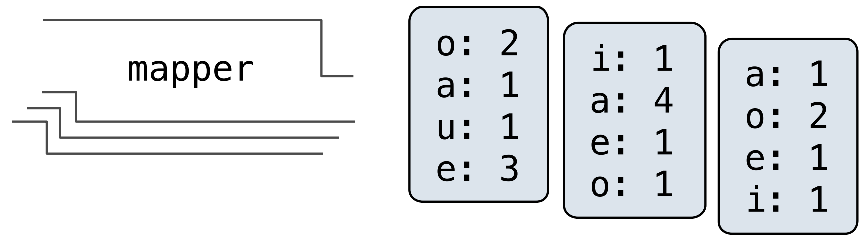

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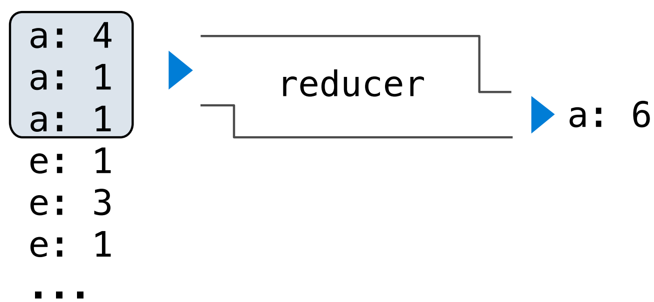

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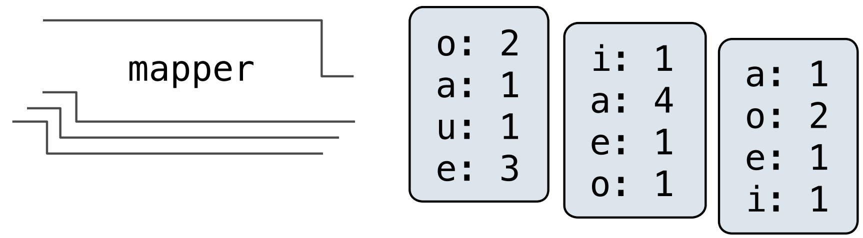

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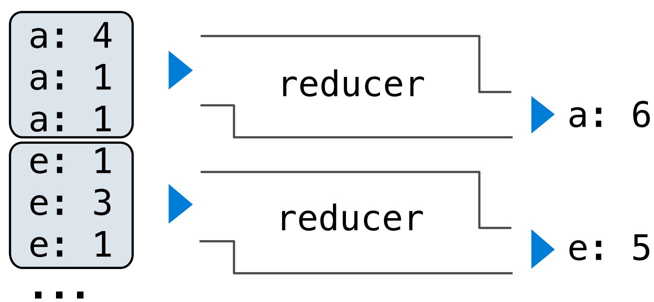
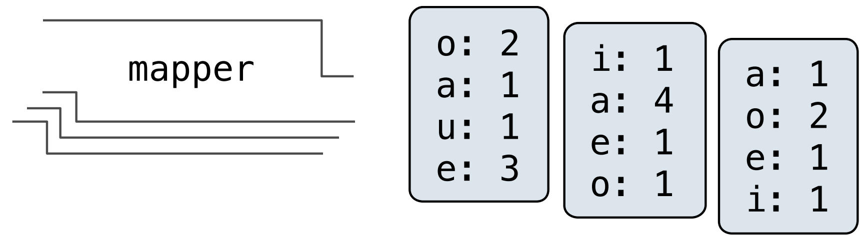


MapReduce Evaluation Model

Google MapReduce
Is a Big Data framework
For batch processing



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

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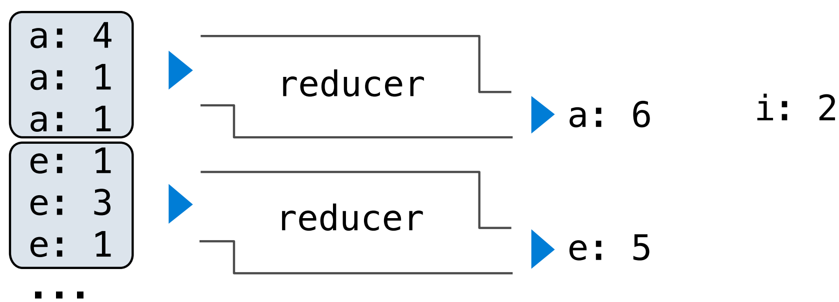

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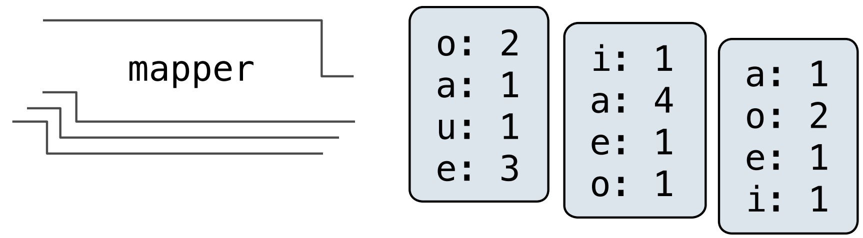

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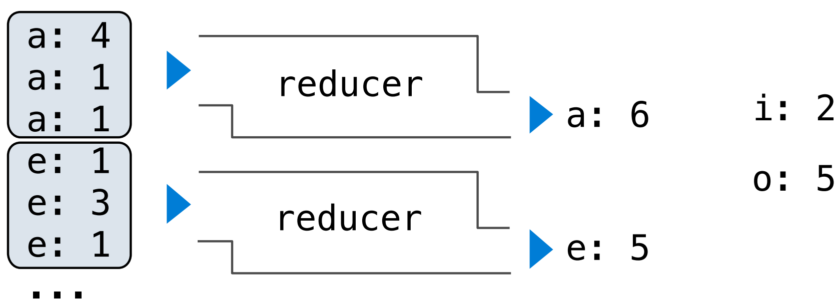

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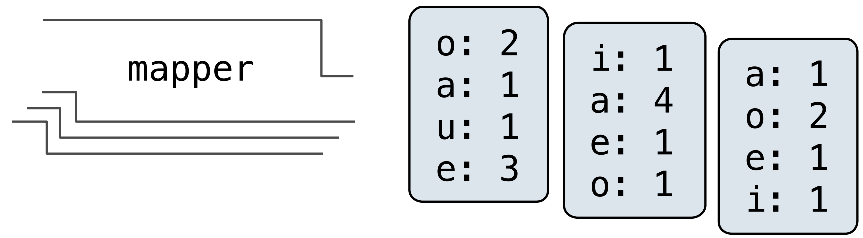

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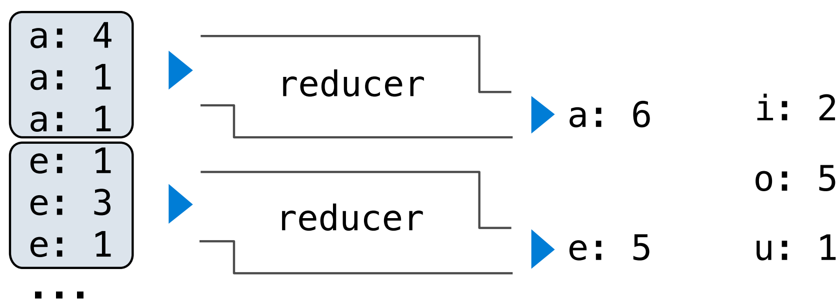

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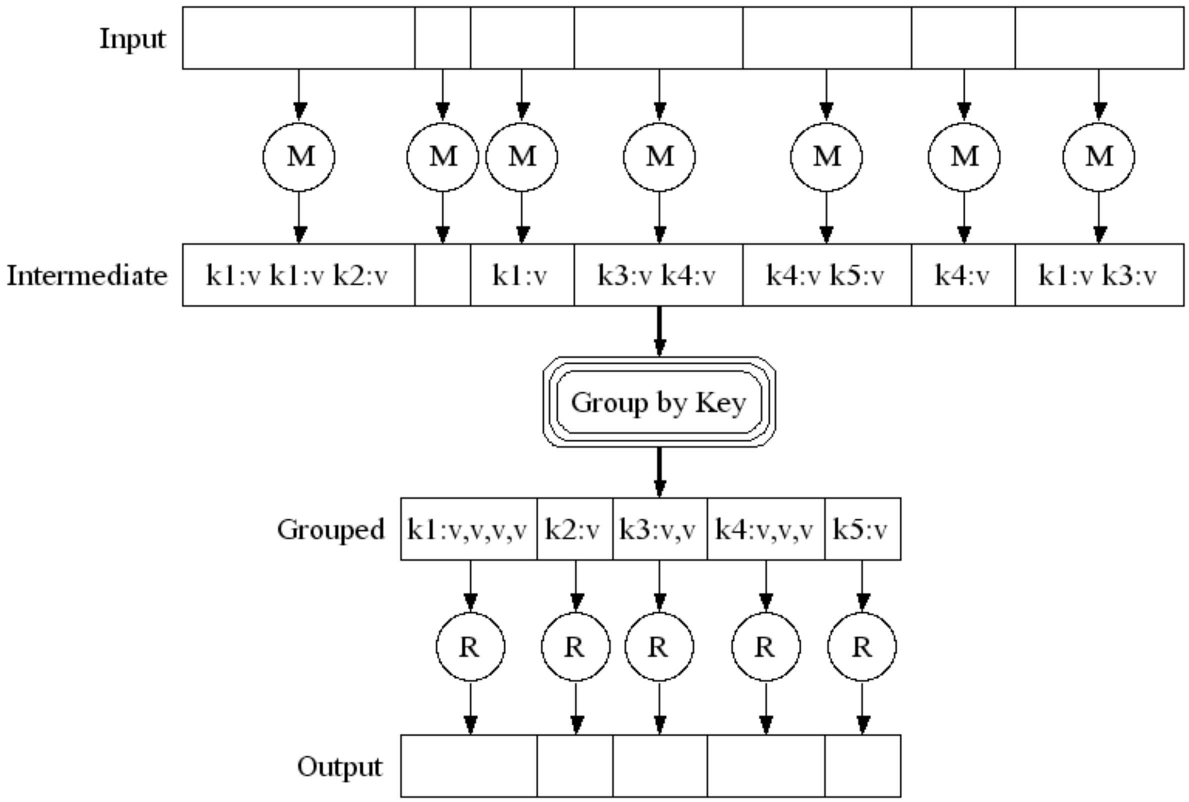

http://research.google.com/archive/mapreduce-osdi04-slides/index-auto-0007.html

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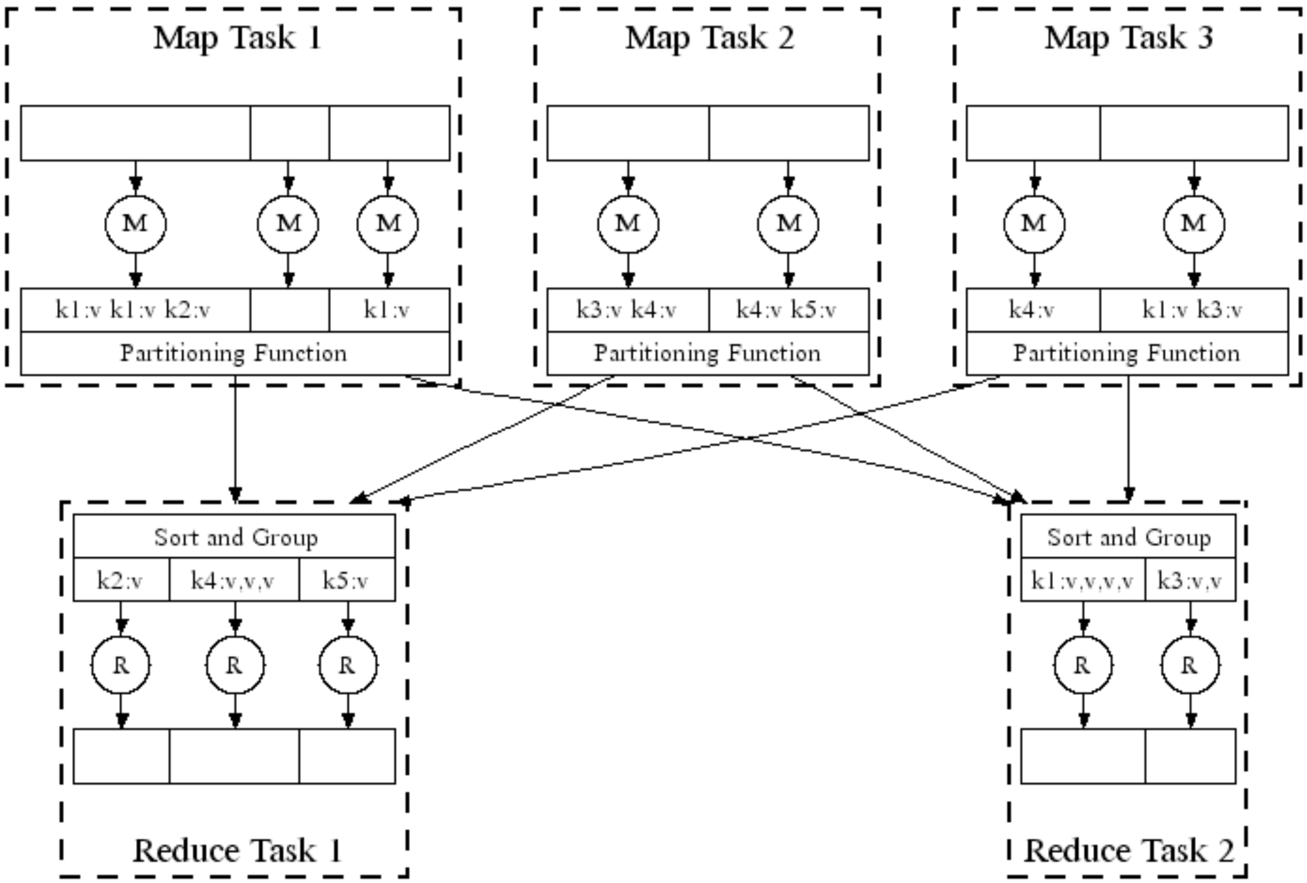

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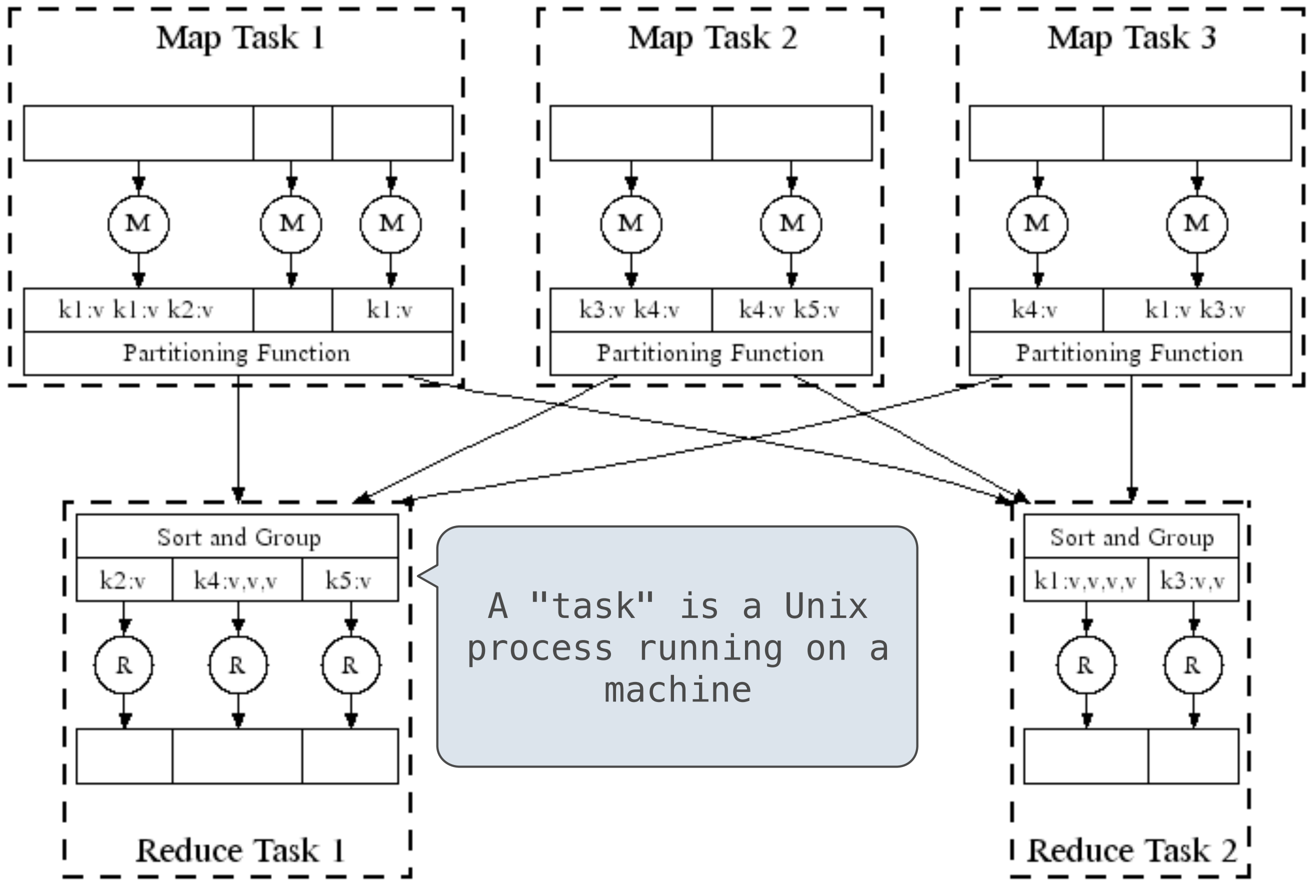

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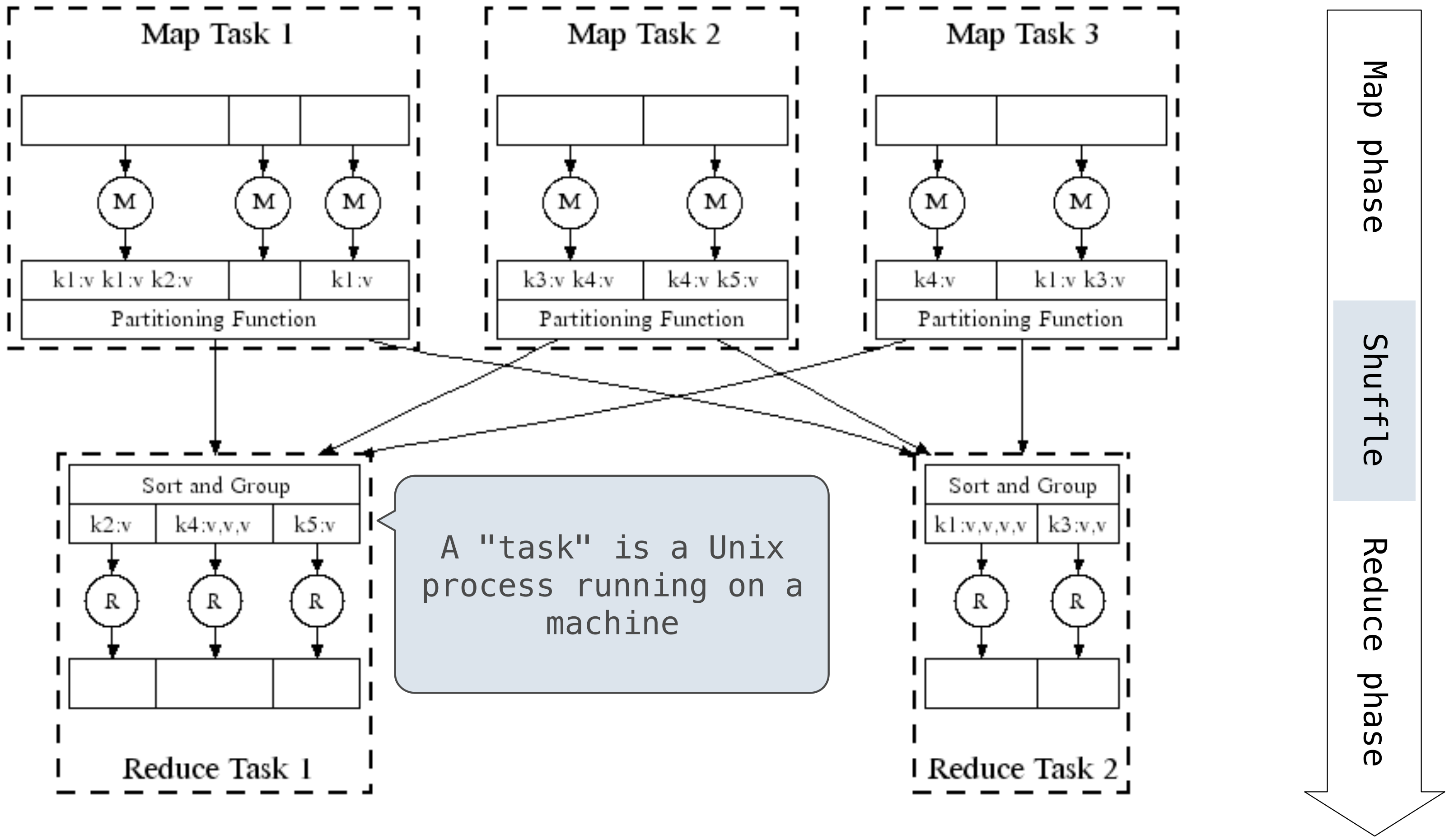

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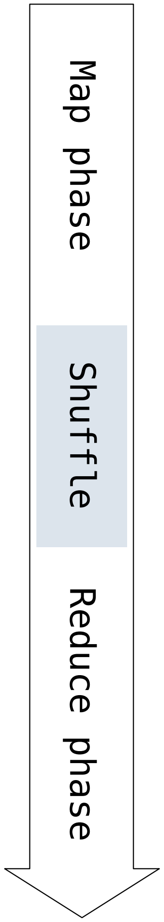

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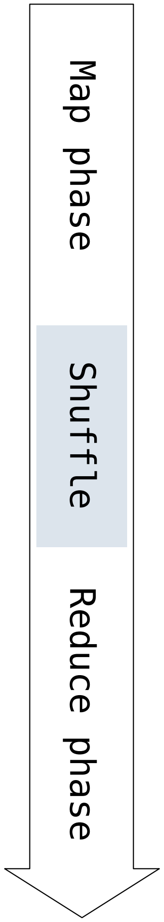

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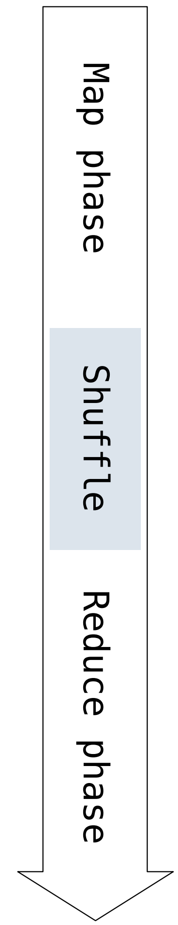

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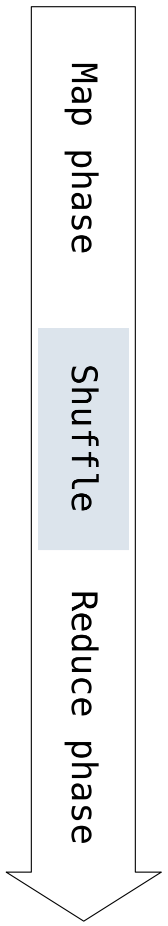

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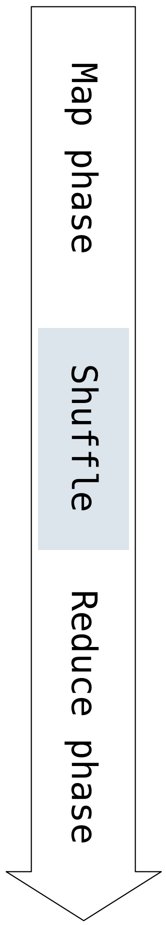

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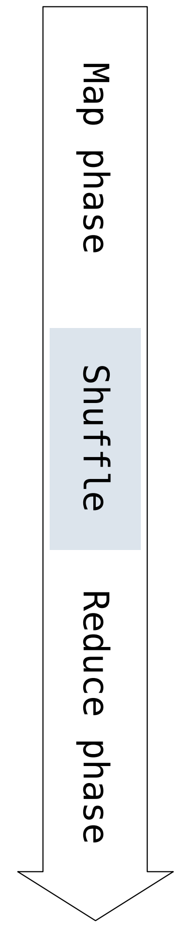

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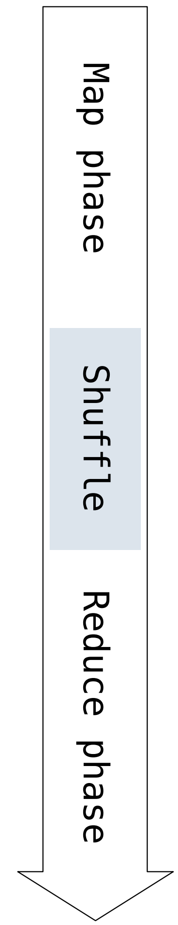

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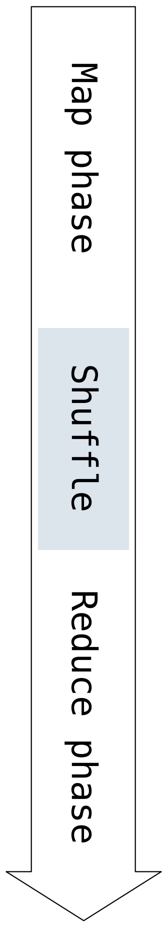

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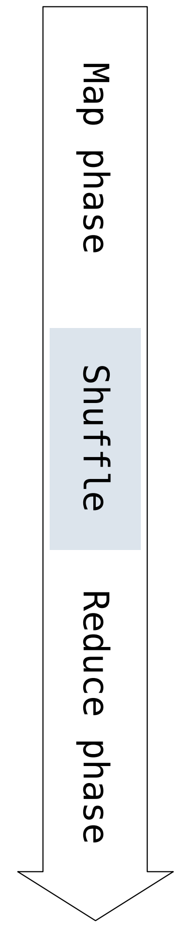

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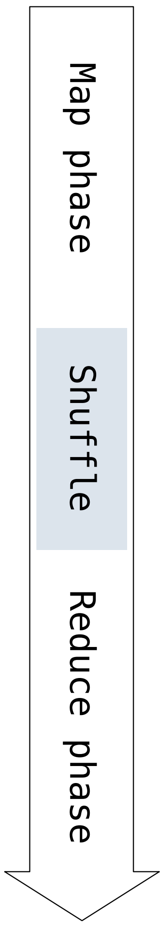

MapReduce Applications

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