61A Lecture 35

Announcements

Unix

Computer Systems

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A unifying property of effective systems:

Hide complexity, but retain flexibility

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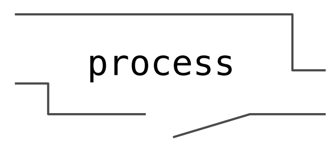

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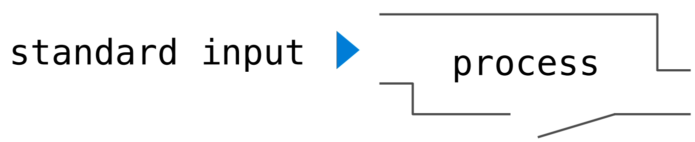

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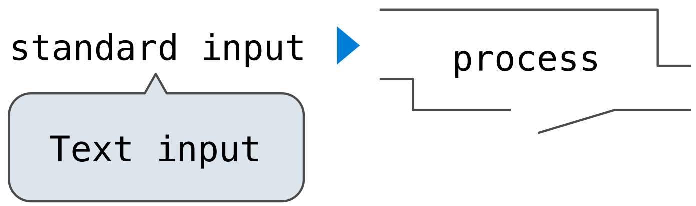

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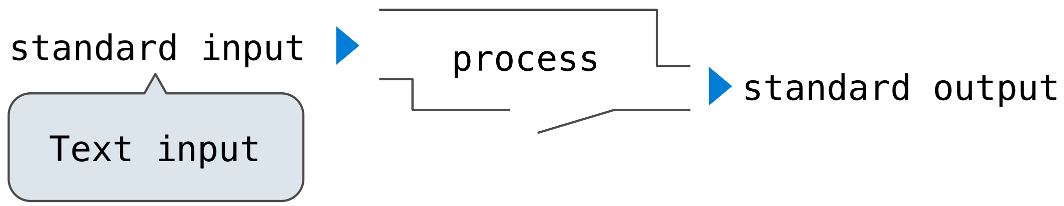

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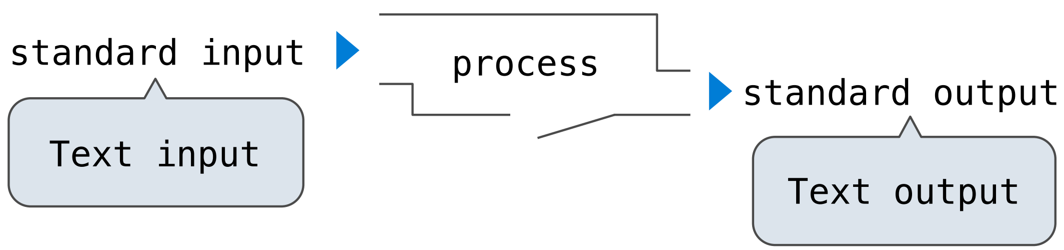

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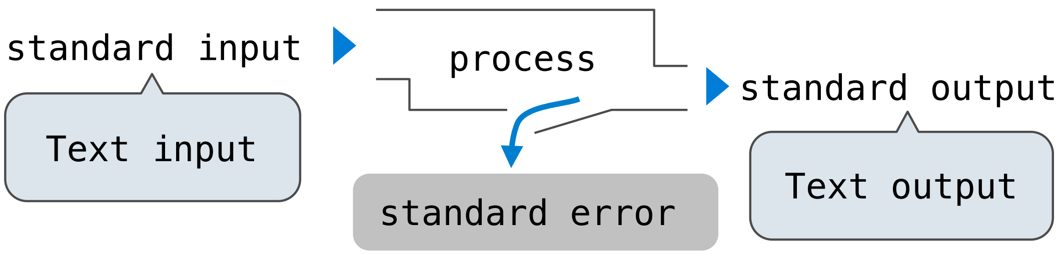

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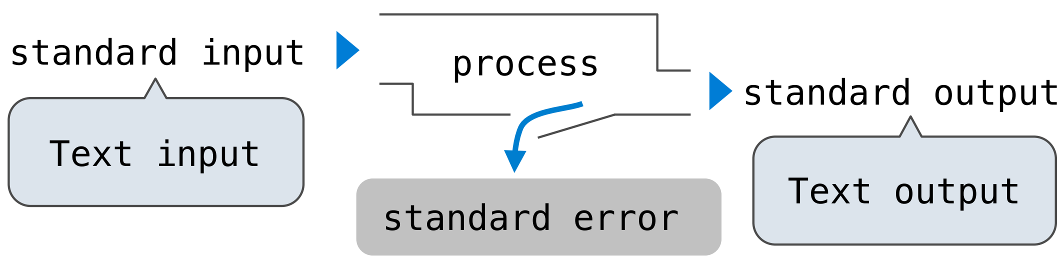

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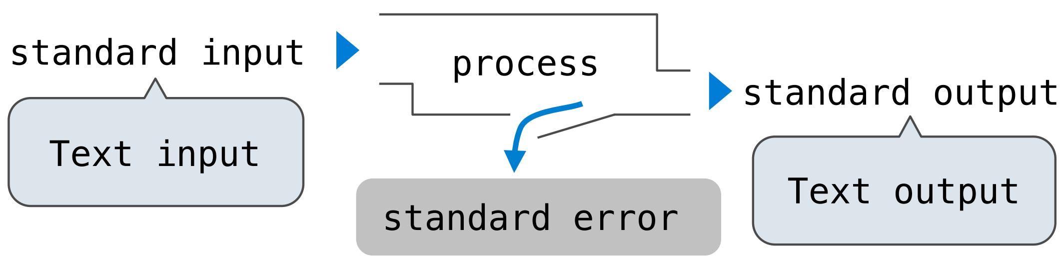

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(Demo)

```
cd ww/assets/slides && ls *.pdf | cut -f 1 -d - | sort -r | uniq -c
```

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Big Data

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Examples from Anthony Joseph

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- When using many computers, some will fail!

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Romeo & Juliet

```
Two households , both alike in dignity ,
In fair Verona , where we lay our scene ,
From ancient grudge break to new mutiny ,
Where civil blood makes civil hands unclean .
From forth the fatal loins of these two foes
A pair of star-cross'd lovers take their life ;
Whose misadventur'd piteous overthrows
Do with their death bury their parents' strife .
The fearful passage of their death-mark'd love ,
And the continuance of their parents' rage ,
Which , but their children's end , nought could remove ,
Is now the two hours' traffick of our stage ;
The which if you with patient ears attend ,
What here shall miss , our toil shall strive to mend .
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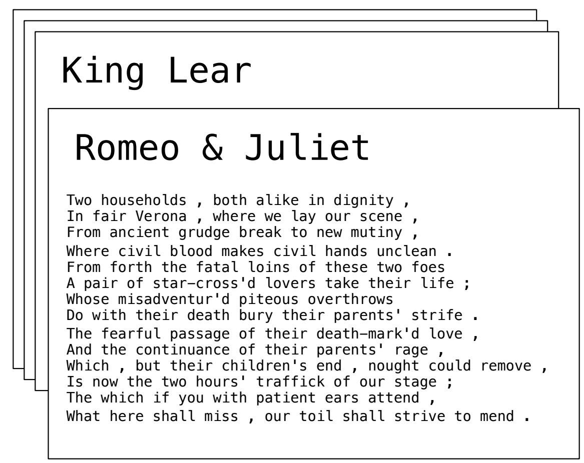
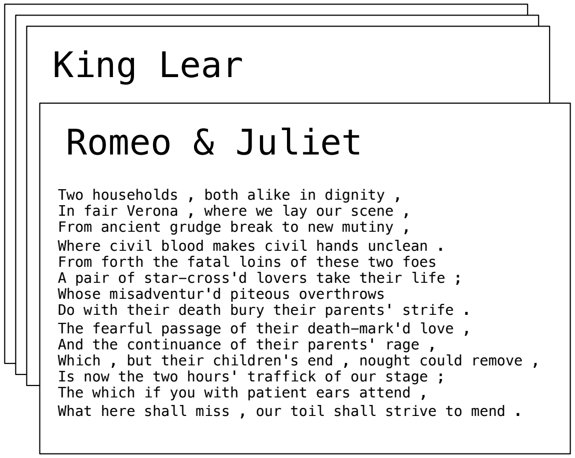


Apache Spark Execution Model



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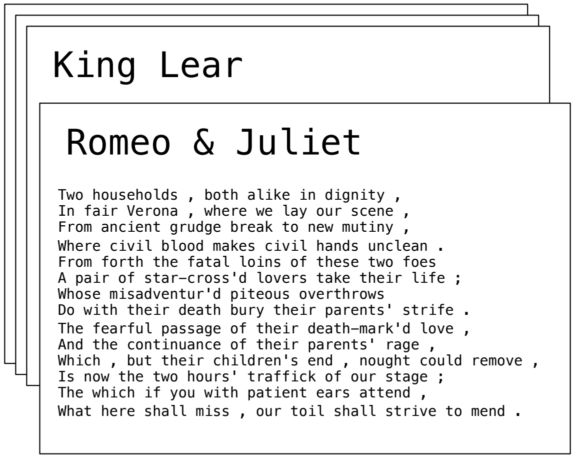

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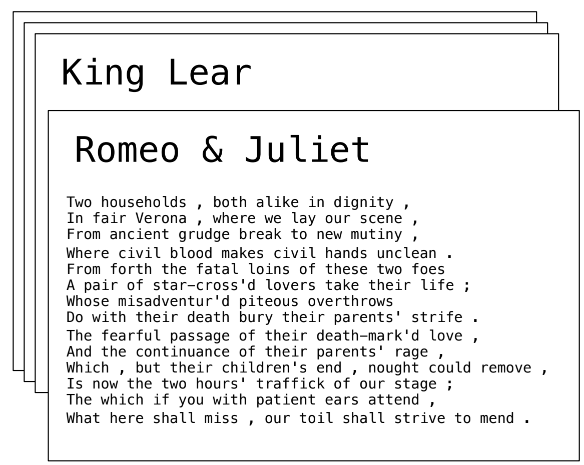

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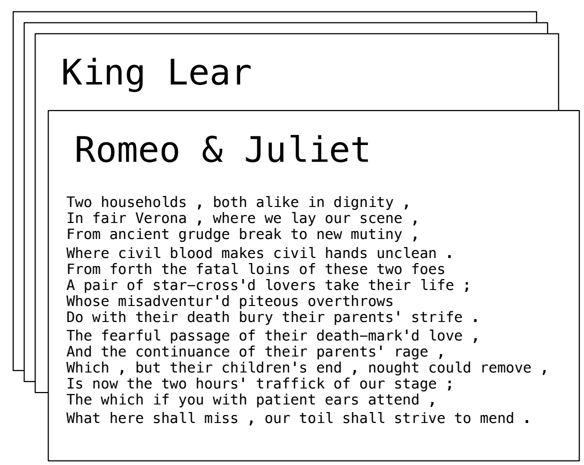

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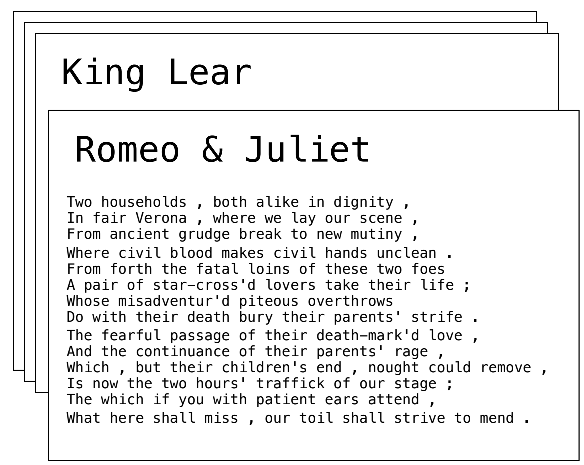

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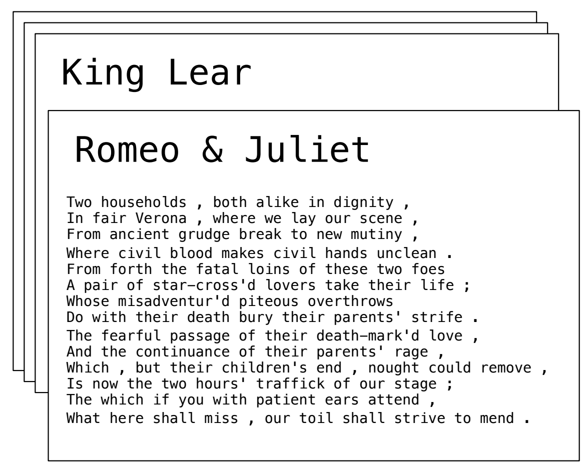

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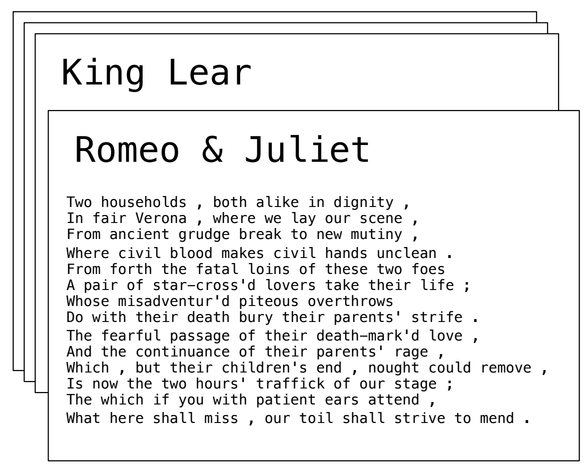

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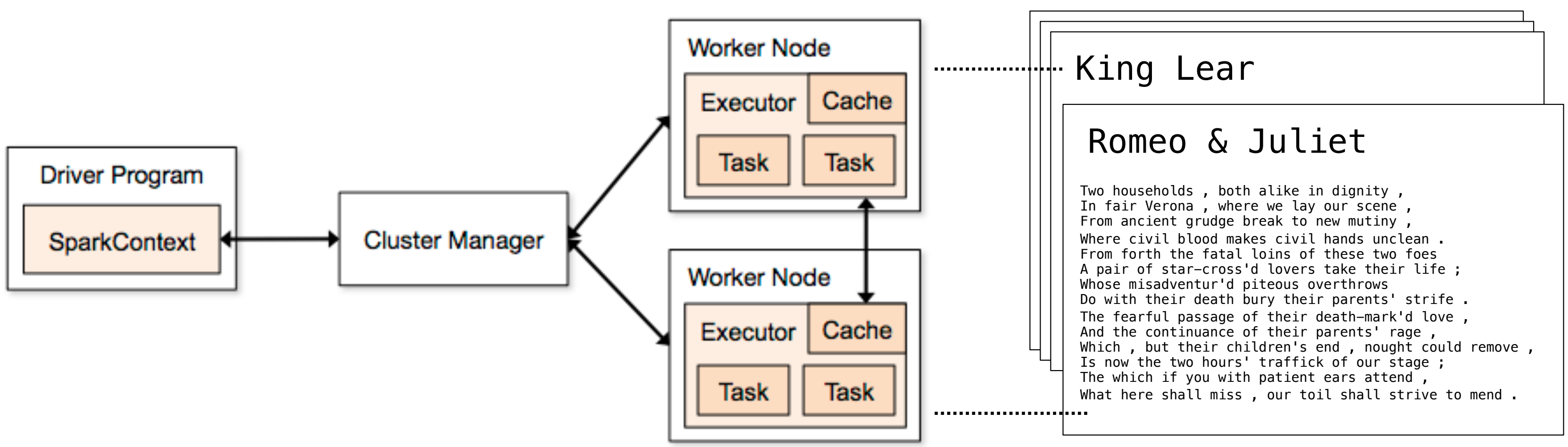

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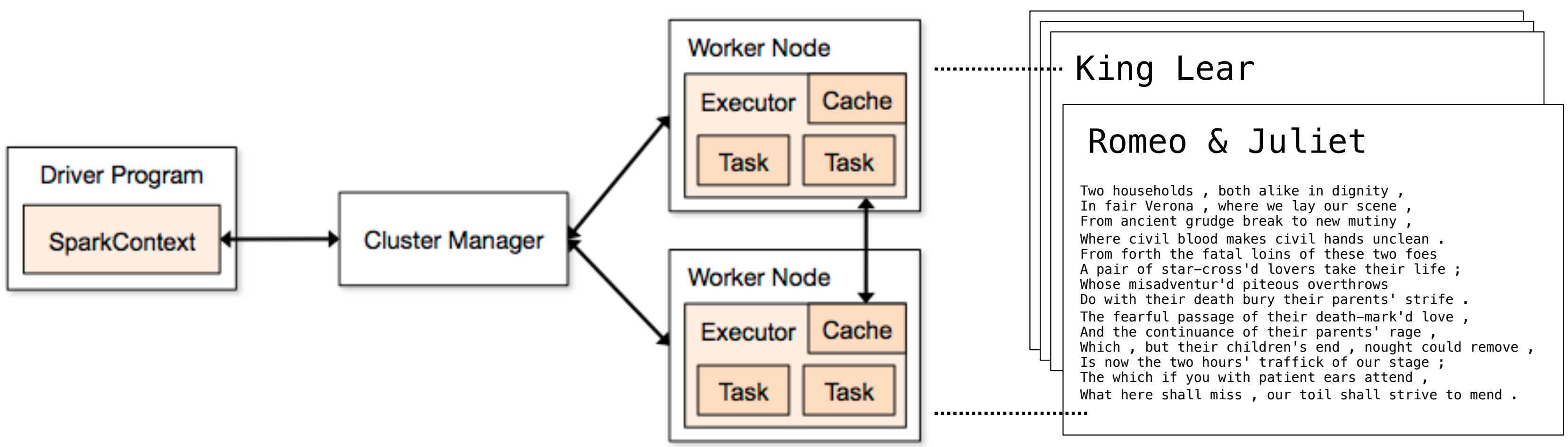

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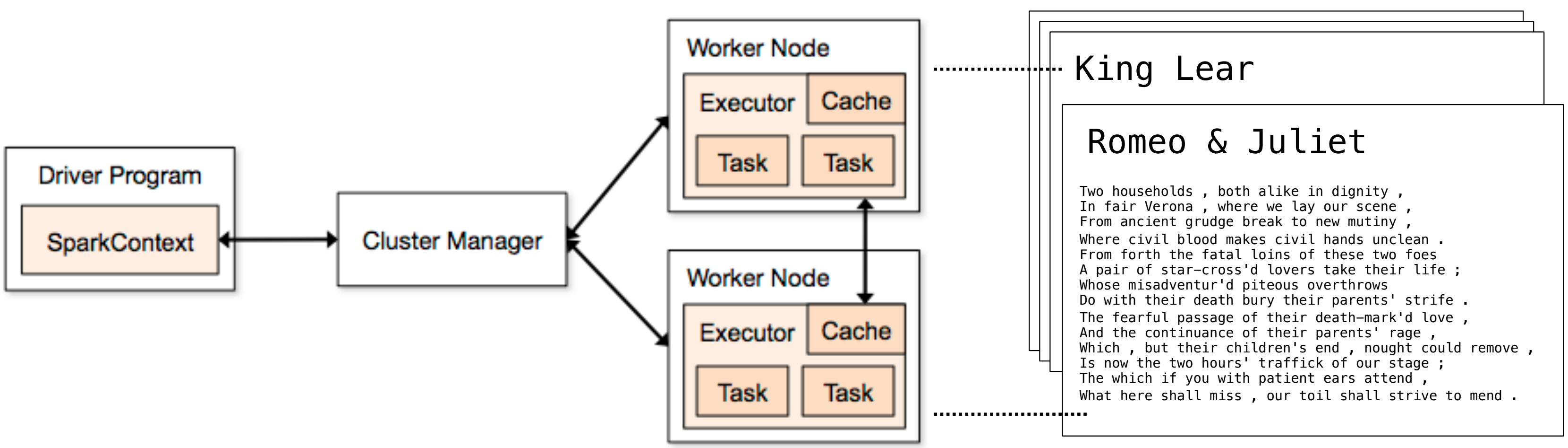

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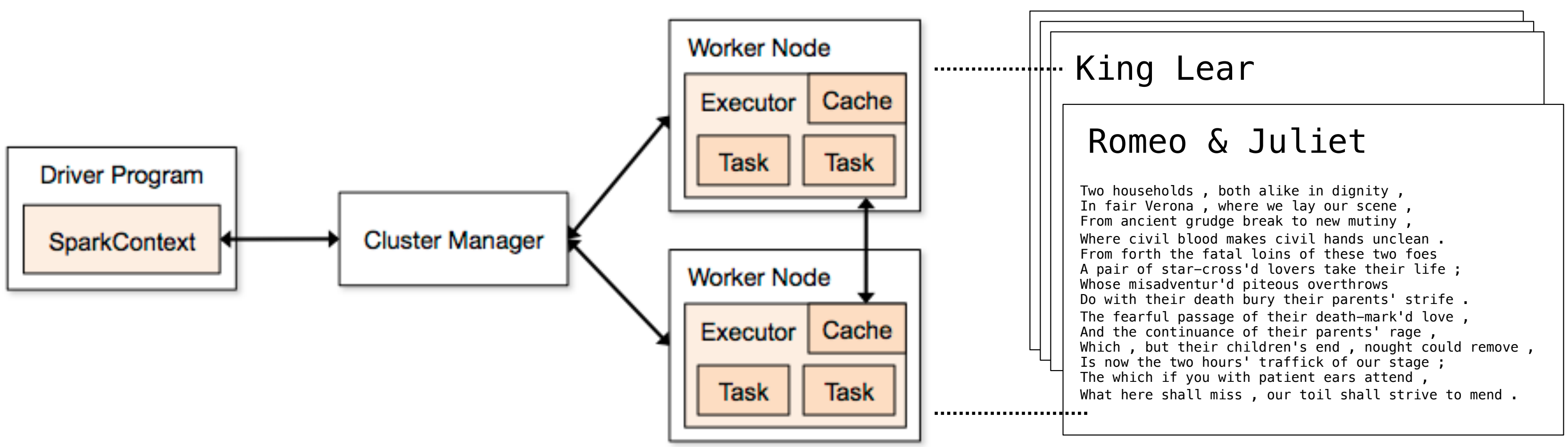

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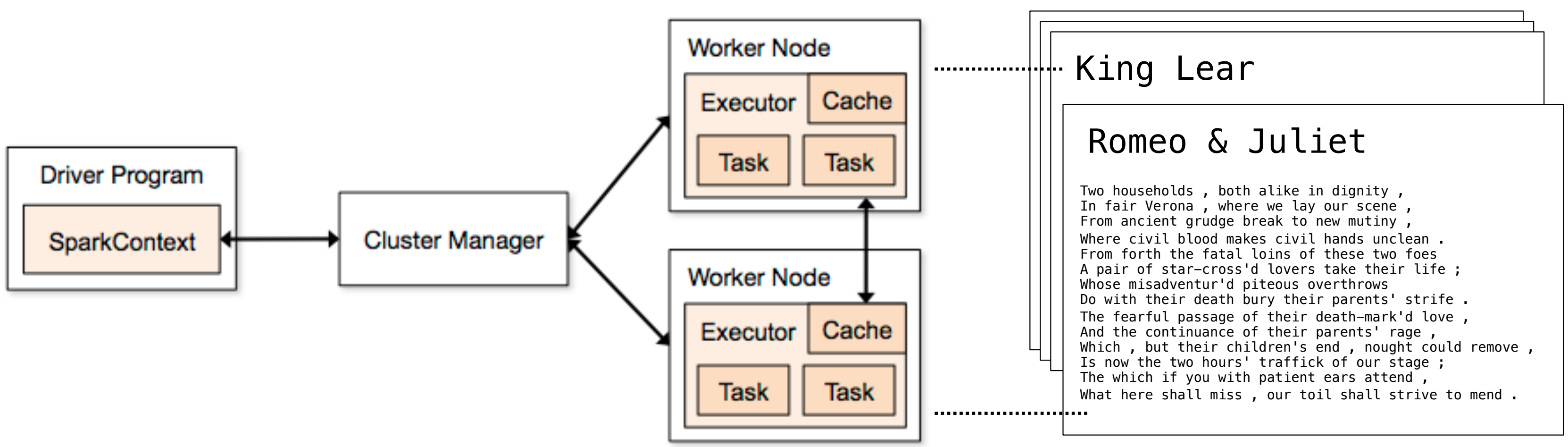

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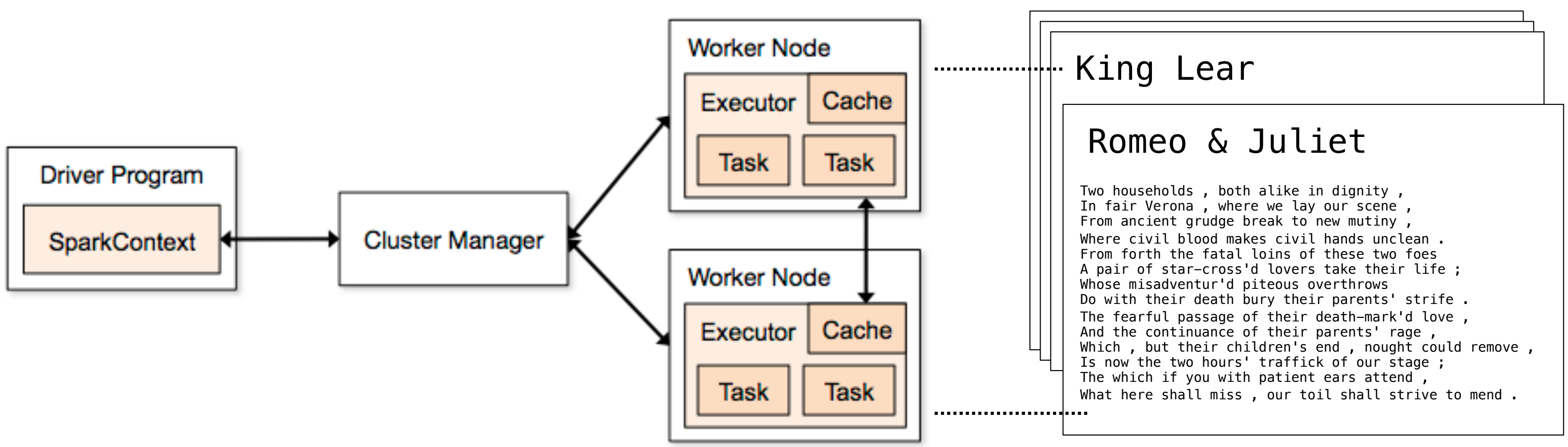

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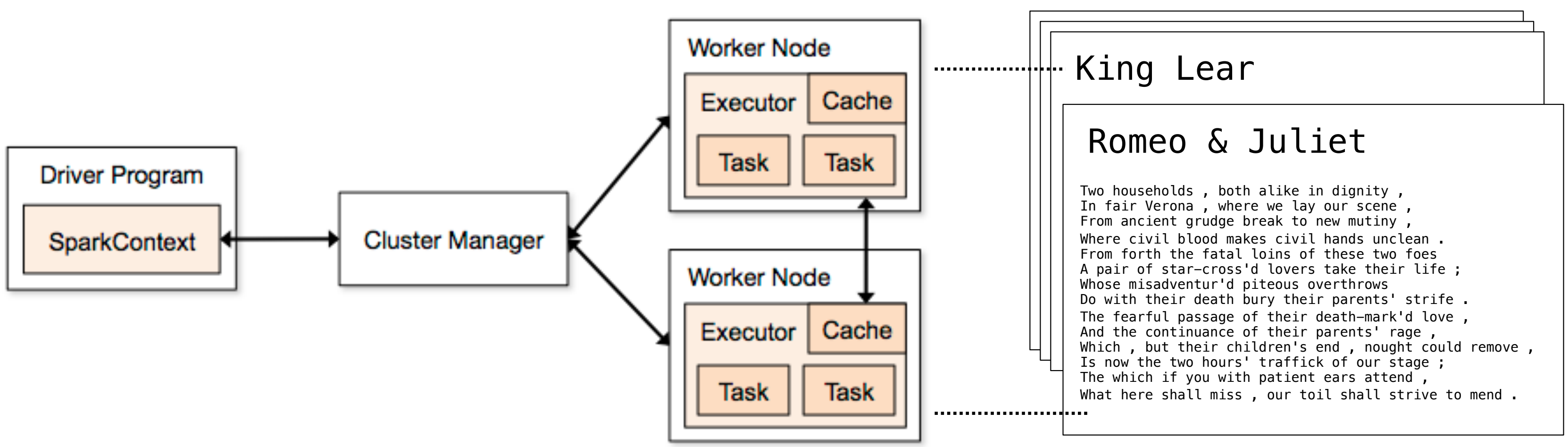

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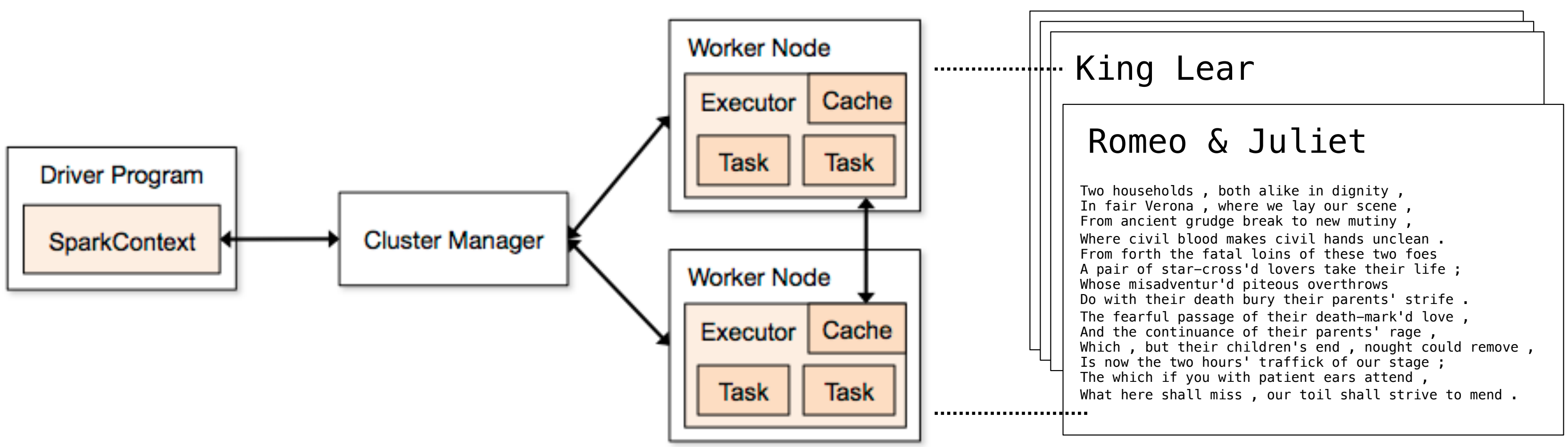

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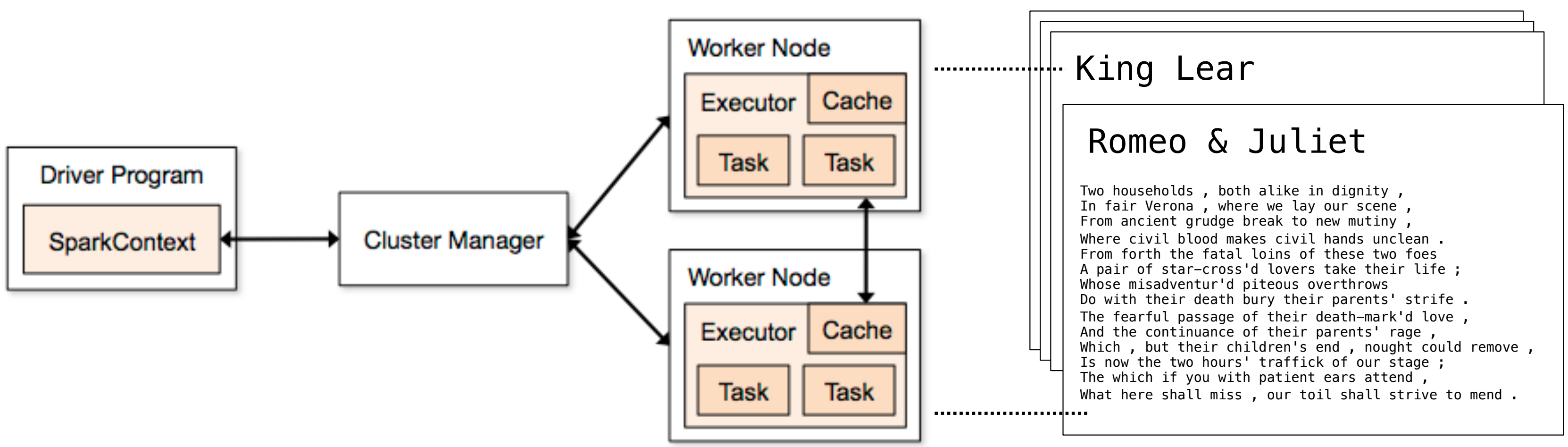

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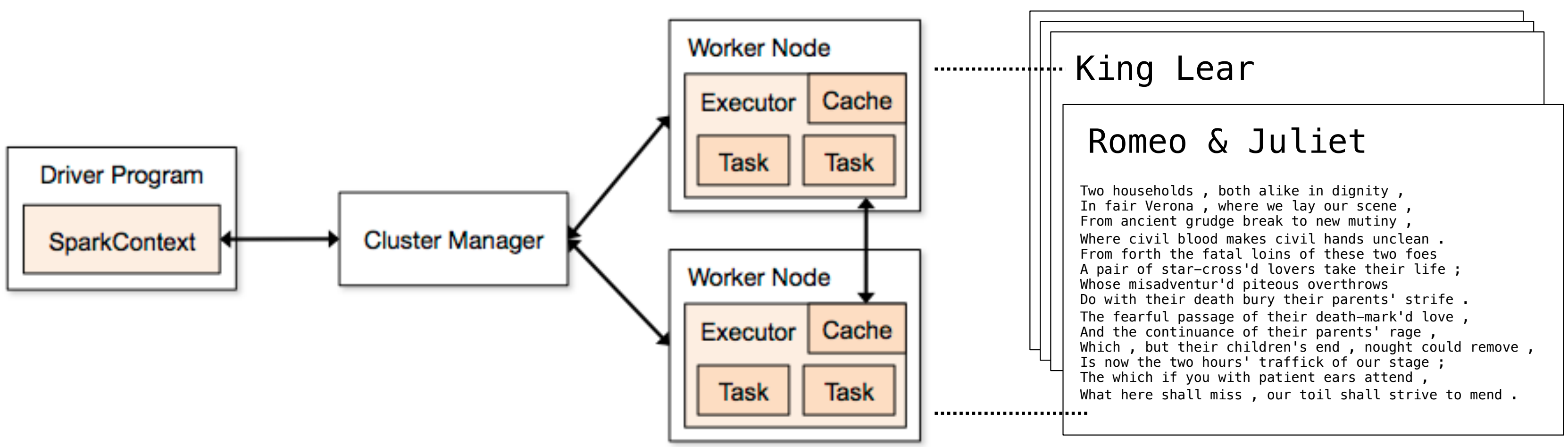

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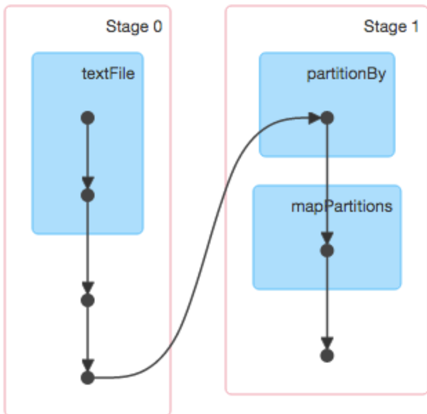

MapReduce

MapReduce Applications

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An important early distributed processing system was MapReduce, developed at Google

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Generic application structure that happened to capture many common data processing tasks

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Early applications: indexing web pages, training language models, & computing PageRank

MapReduce Evaluation Model

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Map phase: Apply a *mapper* function to all inputs, emitting intermediate key-value pairs

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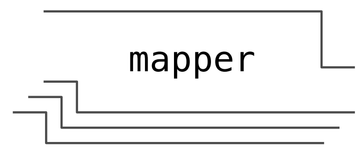


```
o: 2
a: 1
u: 1
e: 3
```

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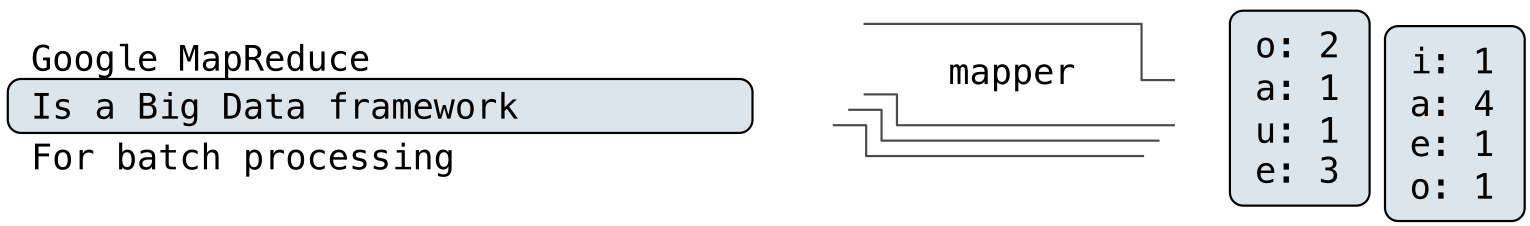

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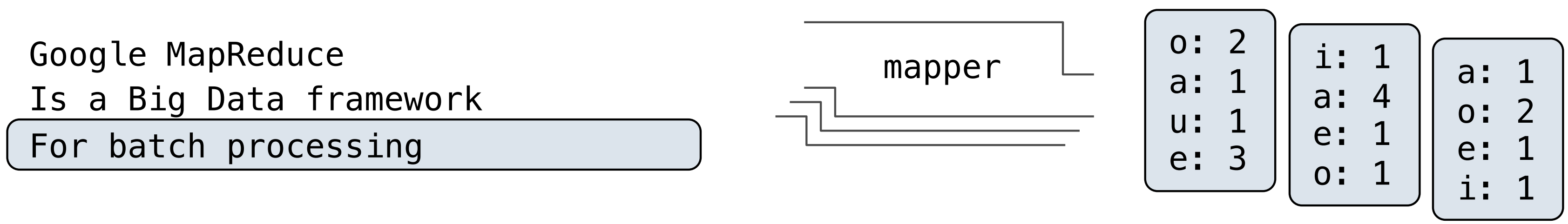

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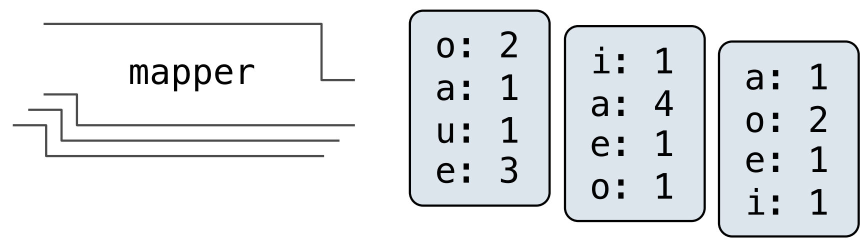

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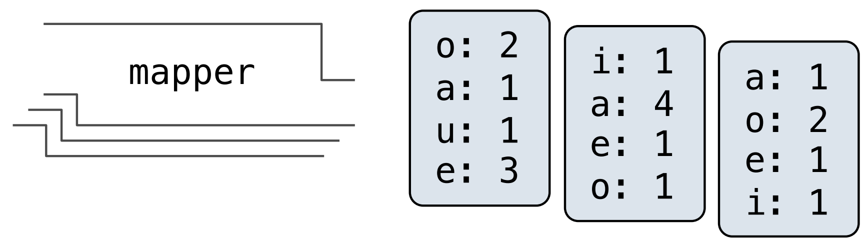

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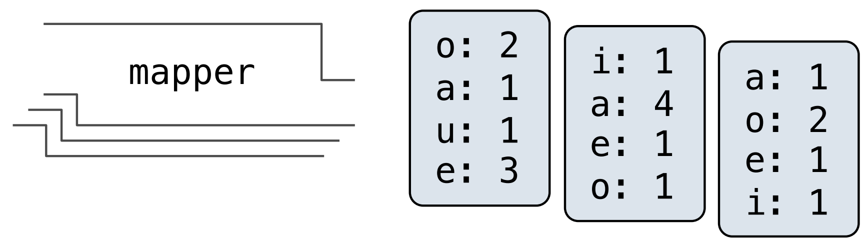

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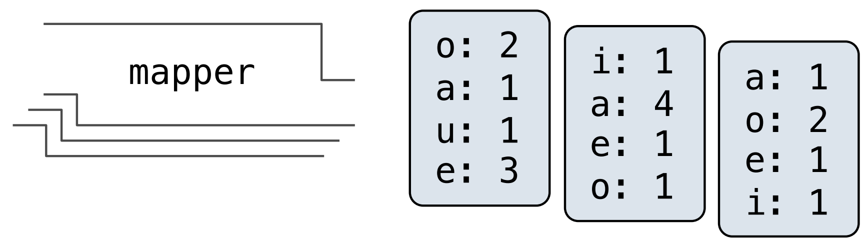

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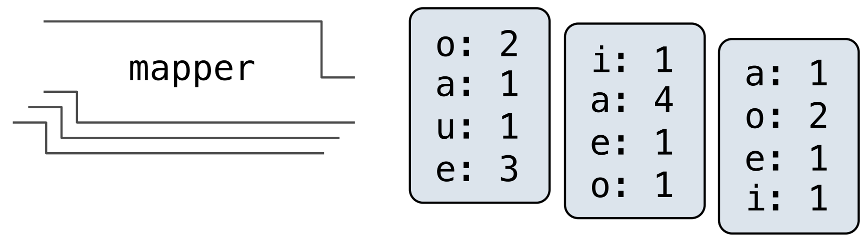

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```
o: 2    i: 1    a: 1
a: 1    a: 4    o: 2
u: 1    e: 1    e: 1
e: 3    o: 1    i: 1
```

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```
a: 4
a: 1
a: 1
e: 1
e: 3
e: 1
...
```

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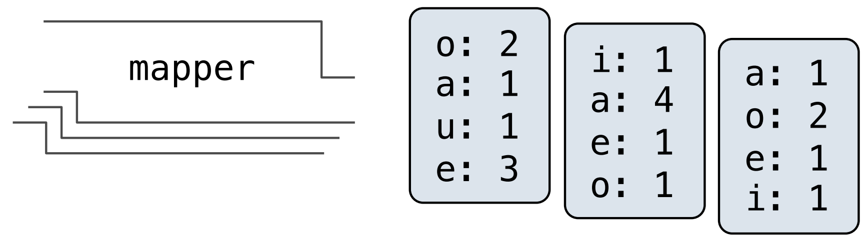

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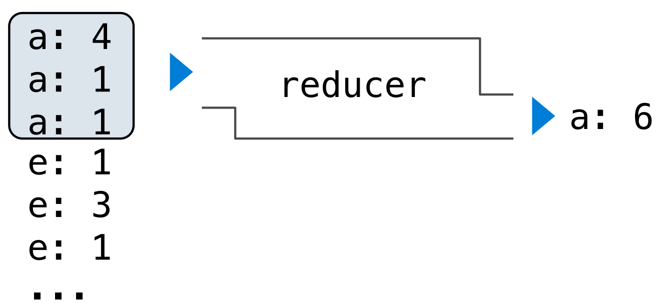

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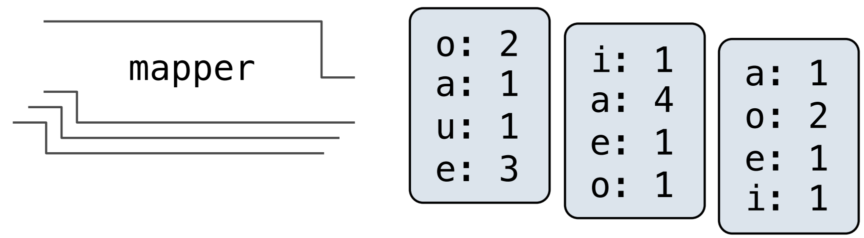

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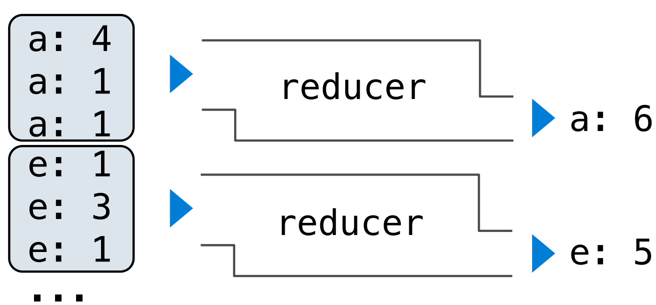

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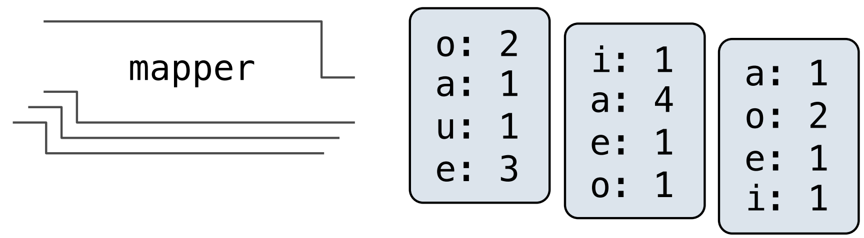

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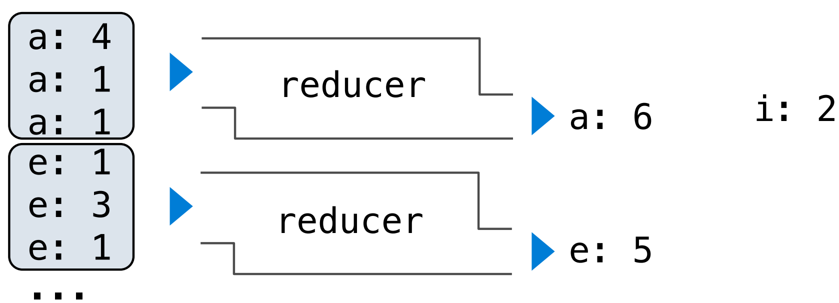

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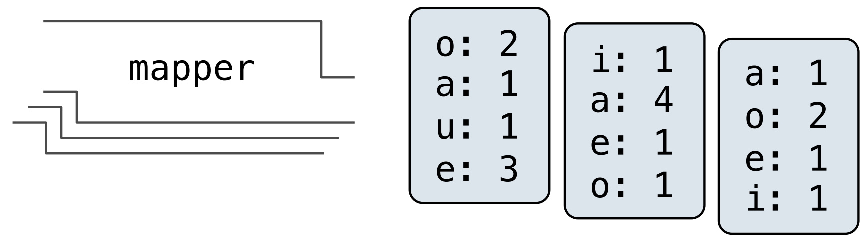

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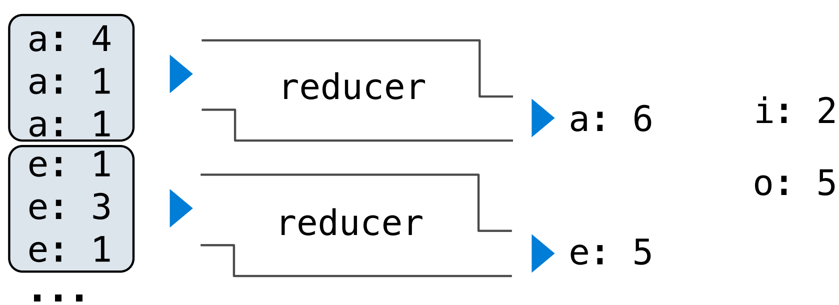

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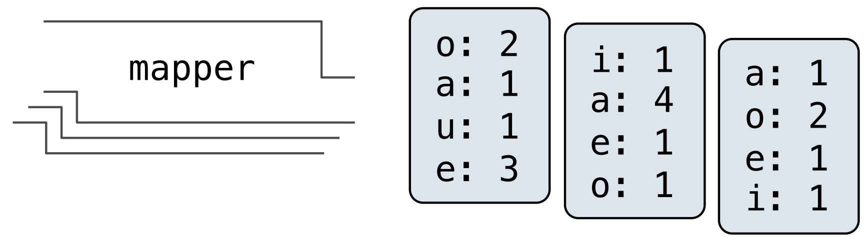

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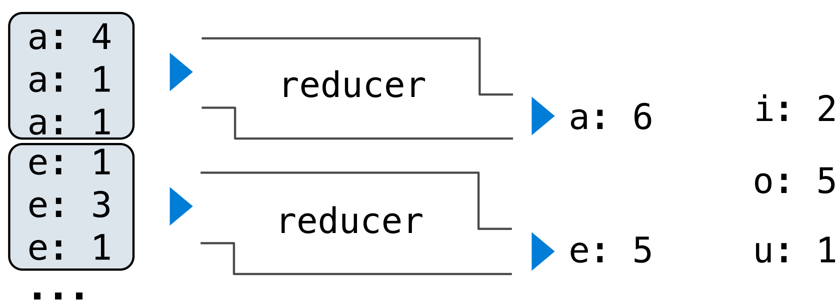

MapReduce Applications on Apache Spark

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Key-value pairs are just two-element Python tuples
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Call Expression

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(Demo)