Lecture 26: Parallelism

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August 4, 2016

Announcements

- Project 4 is due tomorrow (8/5)
  - Submit by today for 1 EC point
- Final Review tomorrow (8/5) from 11–12:30pm in 2050 VLSB
  - Final Exam on Friday (8/12) from 5–8pm in 155 Dwinelle
- Ants composition revisions due Saturday (8/6)
- Scheme Recursive Art Contest is open! Submissions due 8/9
- **Potluck II** on 8/10! 5–8pm (or later) in Wozniak Lounge
  - Bring food and board games!
- Homework 10 will be due 8/9
- Homework 11 and 12 will be due 8/10 and 8/12
  - Last two of the three extra credit surveys

Roadmap

Introduction

Functions

Data

Mutability

Objects

Interpretation

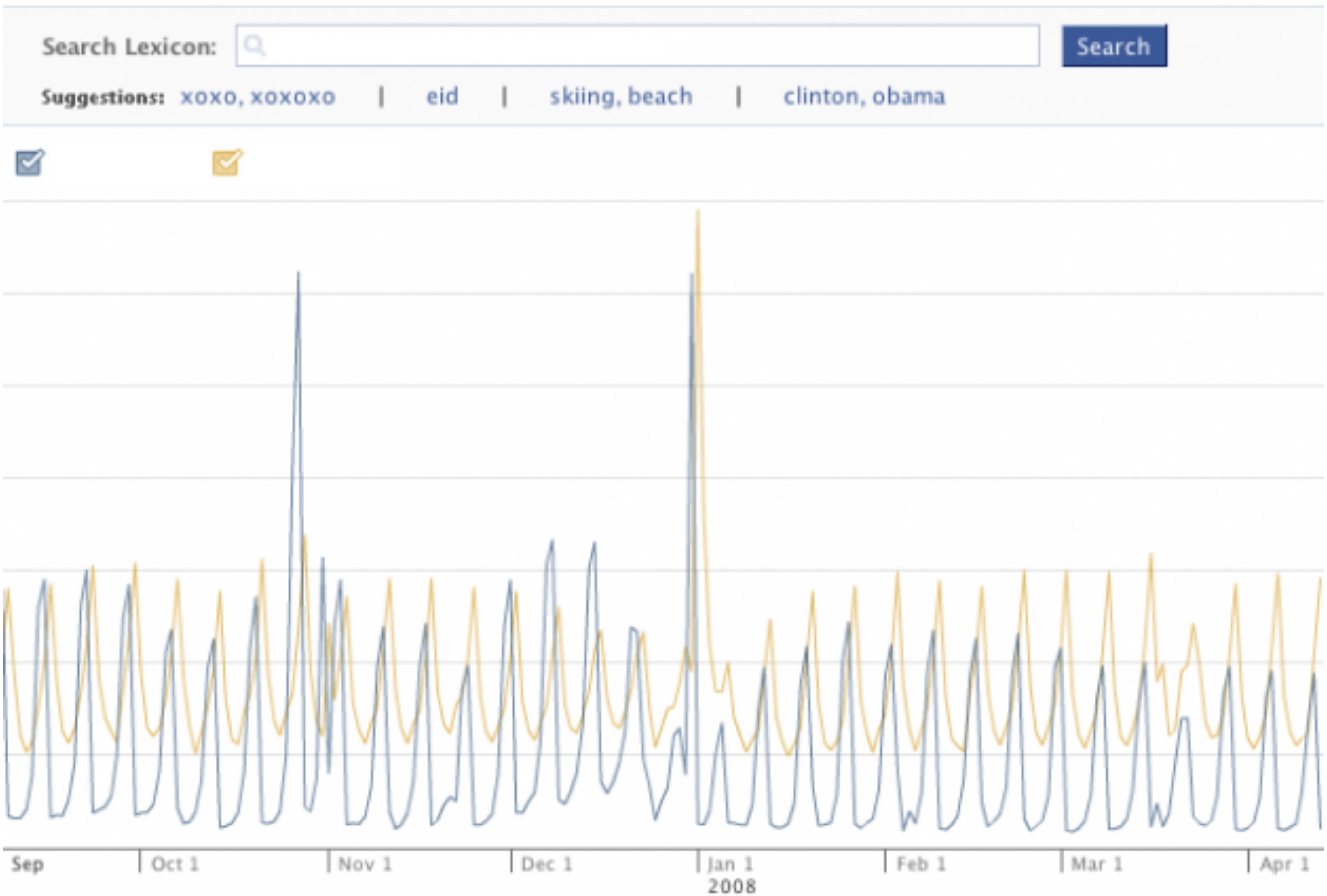
Paradigms

Applications

- This week (Paradigms), the goals are:
  - To study examples of paradigms that are very different from what we have seen so far
  - To expand our definition of what counts as programming

Big Data

Facebook Lexicon



(discontinued)

Examples of Big Data

- There's a lot of data out there!
  - Facebook's daily logs: 60 Terabytes (60,000 Gigabytes)
  - 1,000 genomes project: 200 Terabytes
  - Google web index: 10+ Petabytes (10,000,000 Gigabytes!!)
- These datasets are too large to fit on a single computer
- Reading 1 Terabyte from disk: 3 hours (100 MB per second)

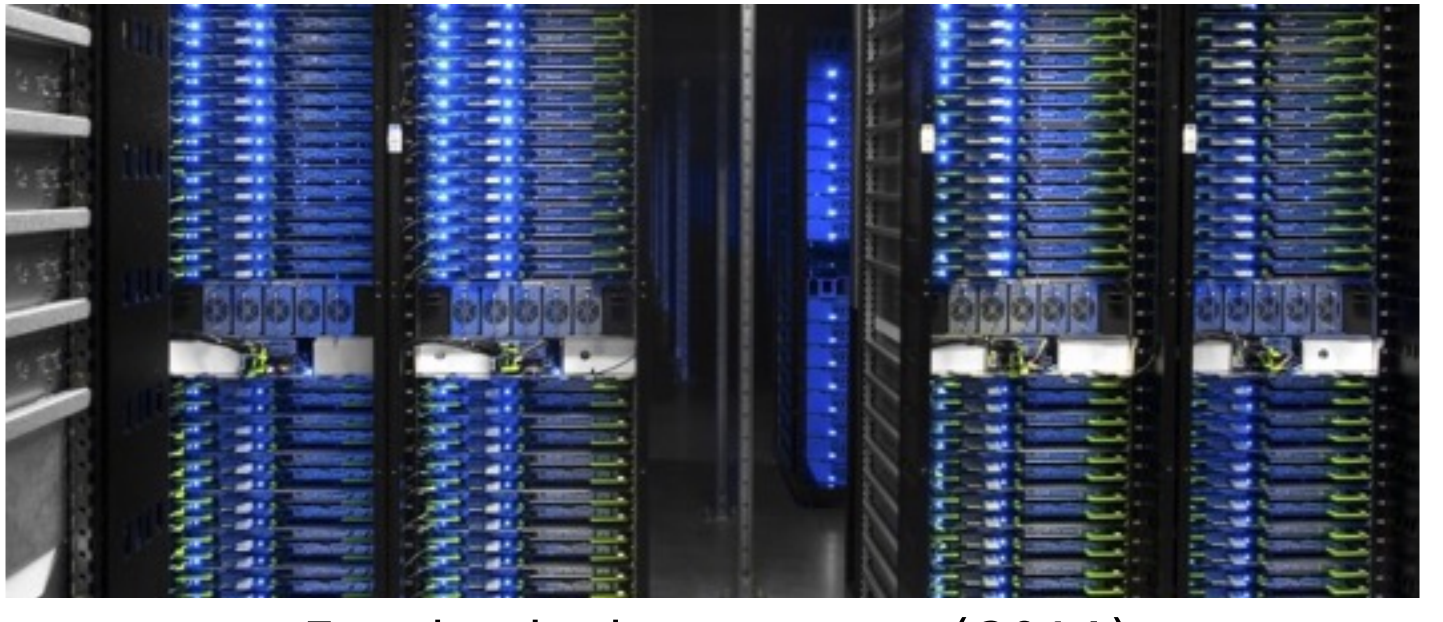
Examples from Anthony Joseph

Distributed Algorithms

- If data can't be stored on a single machine, then our programs can't run on a single machine
- Therefore, we need to develop *distributed algorithms* to distribute and coordinate work between worker machines
- Machines can communicate, but perform computations in their own isolated environment

Computers for Big Data

- Typical hardware for big data applications:
  - Consumer-grade hard disks and processors
  - Independent computers are stored in racks
- Concerns: heat, power, monitoring, networking
- When using many computers, some will fail!



Facebook datacenter (2014)

Distributed Algorithms

- If data can't be stored on a single machine, then our programs can't run on a single machine
- Therefore, we need to develop *distributed algorithms* to distribute and coordinate work between worker machines
- Machines can communicate, but perform computations in their own isolated environment
- Machines and networks occasionally fail!
  - Lost work must be recomputed
- Slow workers should be detected and their task should be given to a different worker
- This is getting complicated...

Apache Spark

Apache Spark

- Apache Spark is a data processing system that provides a simple interface for large data
  - Developed right here at Berkeley in 2010!
- A Resilient Distributed Dataset (RDD) is a collection of values or key–value pairs
- Supports common sequence operations: map, filter, reduce
  - These operations can be performed on RDDs that are partitioned across machines
- Idea: Working with distributed data is complicated. **Use abstraction** to hide the fact that the data is distributed!

Apache Spark Execution Model

- An RDD is distributed in partitions to *worker nodes*
- A *driver program* defines transformations and actions
  - Transformations: Create a new RDD from an existing RDD
  - Actions: Summarize RDD into one value (e.g. sum, take)
- A *cluster manager* assigns tasks to individual *worker nodes* to carry them out
- Worker nodes perform computation and communicate values to each other
- Final results are communicated back to the driver program

The Last Words of Shakespeare

- A *driver program* defines transformations and actions
- A *cluster manager* assigns tasks to individual *worker nodes*
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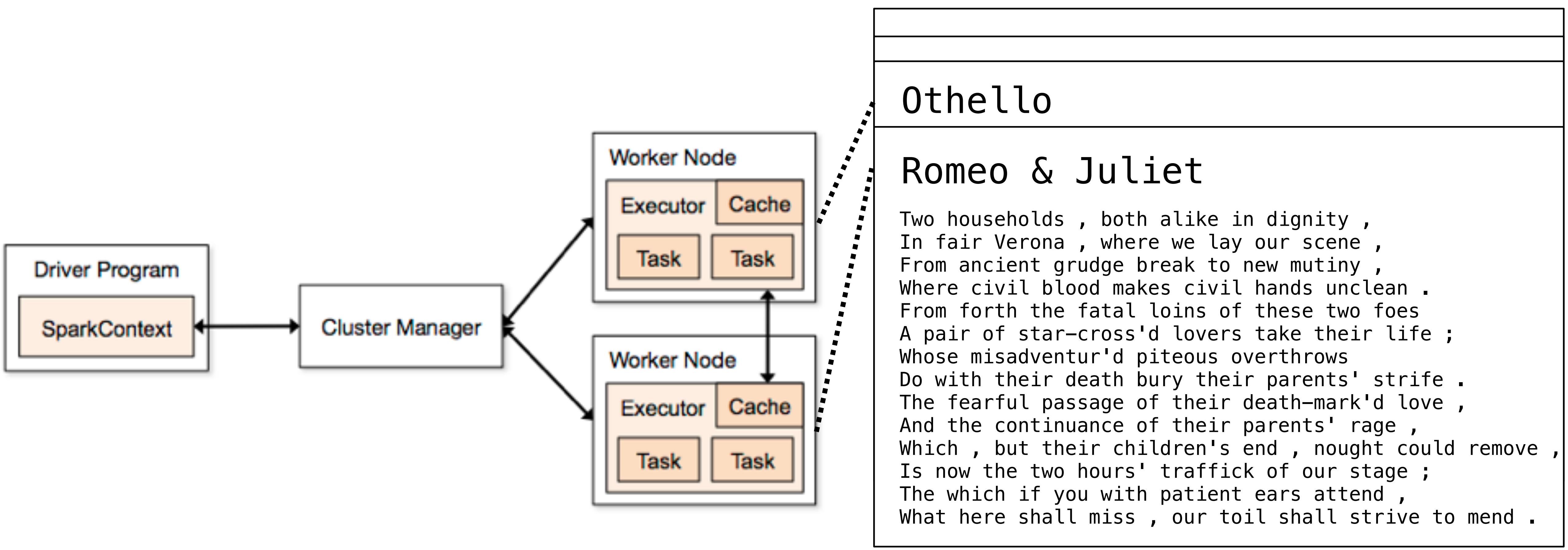


The Last Words of Shakespeare (demo)

- A SparkContext gives access to the cluster manager
- An RDD can be constructed from the lines of a text file
- The sortBy transformation and take action are methods

```
>>> sc
<pyspark.context.SparkContext ...>
>>> shakes = sc.textFile('shakespeare.txt')
>>> shakes.sortBy(lambda line: line, False)
...       .take(2)
['you shall...', 'yet, a...']
```

What Does Apache Spark Provide?

- **Fault tolerance:** A machine or hard drive might crash
    - The cluster manager automatically re-runs failed tasks
- **Speed:** Some machine might be slow because it's overloaded
    - The cluster manager can run multiple copies of a task and keep the result of the one that finishes first
- **Monitoring:** Will my job finish before dinner?!?
    - The cluster manager provides a web-based interface describing jobs
- **Abstraction!**

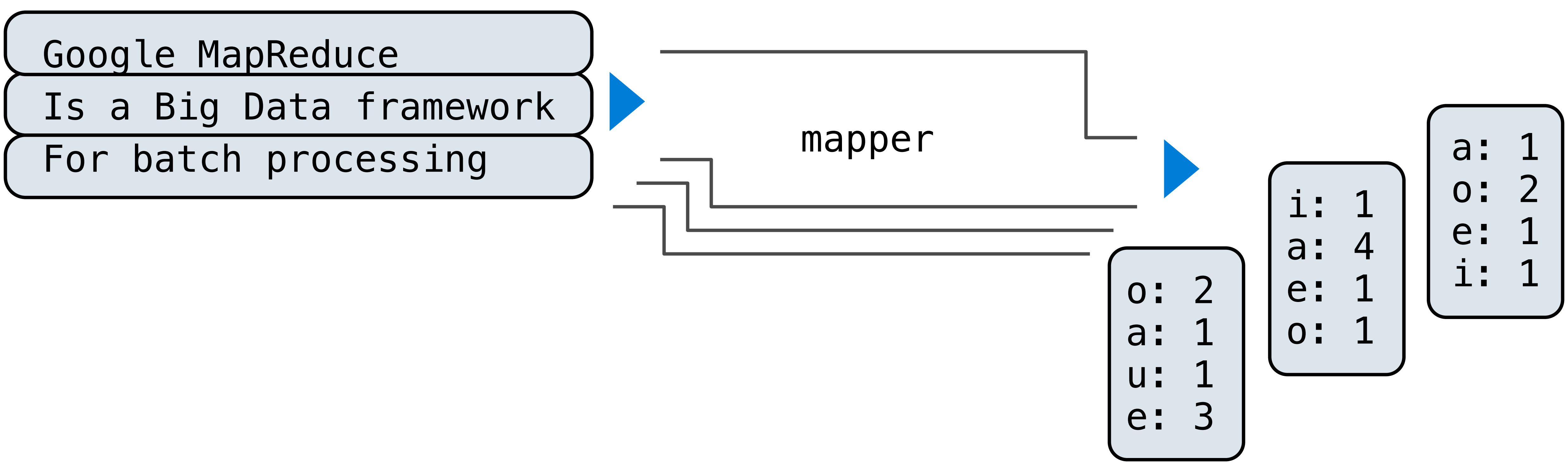
MapReduce

MapReduce Applications

- An important early distributed processing system was MapReduce, published by Google in 2004
- Simple structure that happened to capture many common data processing tasks
  - Step 1: Each element in an input collection produces zero or more key-value pairs (map)
  - Step 2: All key-value pairs that share a key are aggregated together (shuffle)
  - Step 3: All the values for a key are processed as a sequence (reduce)
- Early applications: indexing web pages, computing PageRank

MapReduce Evaluation Model

- Map step: Apply a mapper function to all inputs, emitting intermediate key-value pairs
- Reduce step: For each intermediate key, apply a reducer function to accumulate all values associated with that key
    - All key-value pairs with the same key are processed together



MapReduce Evaluation Model

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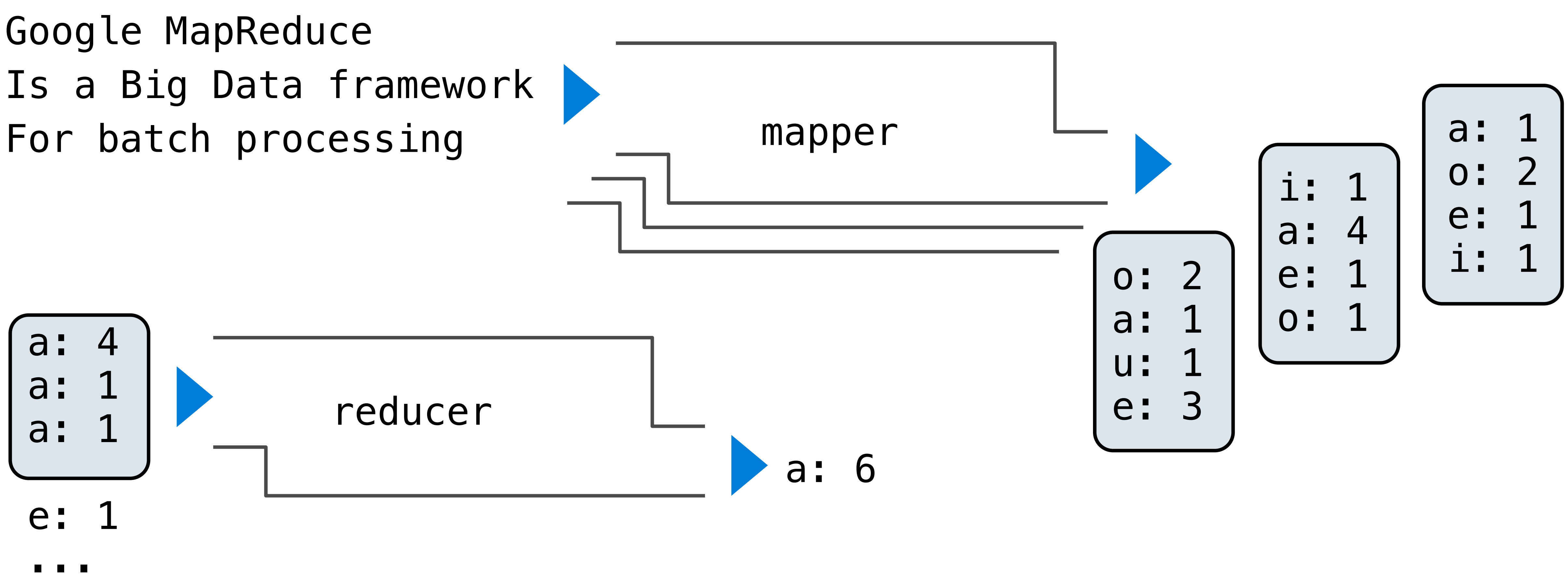

MapReduce on Apache Spark (demo)

Key-value pairs are just two-element Python tuples

Call Expression	**Data**	**fn Input**	**fn Output**	**Result**
data.**flatMap**(fn)	Values	One value	Zero or more key-value pairs	All key-value pairs returned by calls to fn
data.**reduceByKey**(fn)	Key-value pairs	Two values	One value	One key-value pair for each unique key

Summary

- Some problems are too big for one computer to solve!
- However, distributed programming comes with its own issues
- We can use abstractions (such as Apache Spark) to manage some of the complexity that is inevitable when running programs on many machines