61A Lecture 36

Announcements

Unix

#### Computer Systems

Systems research enables application development by defining and implementing abstractions:

- Operating systems provide a stable, consistent interface to unreliable, inconsistent hardware
- ${f Networks}$  provide a robust data transfer interface to constantly evolving communications infrastructure
- $\mbox{\bf Databases}$  provide a declarative interface to complex software that stores and retrieves information efficiently
- Distributed systems provide a unified interface to a cluster of multiple machines

A unifying property of effective systems:

Hide complexity, but retain flexibility

## Example: The Unix Operating System

Essential features of the Unix operating system (and variants):

- ${\boldsymbol{\cdot}}$   ${\boldsymbol{Portability:}}$  The same operating system on different hardware
- $\hbox{\bf Multi-Tasking:} \ \hbox{Many processes run concurrently on a machine}$
- ${\mbox{\ensuremath{\bullet}}}\mbox{\ensuremath{\mathsf{Plain}}}\mbox{\ensuremath{\mathsf{Text}}\mbox{\ensuremath{\bullet}}}\mbox{\ensuremath{\mathsf{Data}}}\mbox{\ensuremath{\mathsf{a}$
- Modularity: Small tools are composed flexibly via pipes

"We should have some ways of coupling programs like [a] garden hose — screw in another segment when it becomes necessary to massage data in another way," Doug McIlroy in 1964.



The standard streams in a Unix-like operating system are similar to Python iterators  $({\tt Demo})$ 

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

#### Python Programs in a Unix Environment

The sys.stdin and sys.stdout values provide access to the Unix standard streams as files

A Python file has an interface that supports iteration, read, and write methods

Using these "files" takes advantage of the operating system text processing abstraction

The input and print functions also read from standard input and write to standard output

(Demo)

Big Data

#### Big Data Examples

Facebook's daily logs: 60 Terabytes (60,000 Gigabytes)

1,000 genomes project: 200 Terabytes

Google web index: 10+ Petabytes (10,000,000 Gigabytes)

Time to read 1 Terabyte from disk: 3 hours (100 Megabytes/second)

Typical hardware for big data applications:

Consumer-grade hard disks and processors

Independent computers are stored in racks

Concerns: networking, heat, power, monitoring

When using many computers, some will fail!



Facebook datacenter (2014)

Examples from Anthony Joseph

# Apache Spark

#### Apache Spark

Apache Spark is a data processing system that provides a simple interface for large data

- A Resilient Distributed Dataset (RDD) is a collection of values or key-value pairs
- Supports common UNIX operations: sort, distinct (uniq in UNIX), count, pipe
- · Supports common sequence operations: map, filter, reduce
- · Supports common database operations: join, union, intersection

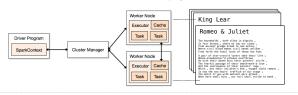
All of these operations can be performed on RDDs that are partitioned across machines



#### Apache Spark Execution Model

Processing is defined centrally but executed remotely

- $^{\circ}$  A Resilient Distributed Dataset (RDD) is distributed in partitions to worker nodes
- $\,\,{}^{\circ}\,\text{A}$  driver program defines transformations and actions on an RDD
- $\,{}^{_{\mathrm{o}}}\,\mathrm{A}$   $\,\mathit{cluster}$  manager assigns tasks to individual  $\mathit{worker}$   $\mathit{nodes}$  to carry them out
- ·Worker nodes perform computation & communicate values to each other
- Final results are communicated back to the driver program



# Apache Spark Interface

The Last Words of Shakespeare (Demo)

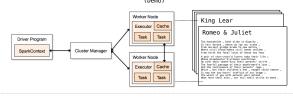
A  $\ensuremath{\mathsf{SparkContext}}$  gives access to the cluster manager

A RDD can be constructed from the lines of a text file >>> x = sc.textFile('shakespeare.txt')

The sortBy transformation and take action are methods

(Demo)

>>> x.sortBy(lambda s: s, False).take(2)



## 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

 $^{\circ}$  The cluster manager can run multiple copies of a task and keep the result of the one that finishes first

Network locality: Data transfer is expensive

\*The cluster manager tries to schedule computation on the machines that hold the data to be processed

Monitoring: Will my job finish before dinner?!?

The cluster manager provides a web-based interface describing jobs  $% \left( \frac{1}{2}\right) =\frac{1}{2}\left( \frac{1}{2}\right) +\frac{1}{2}\left( \frac{1}{2}\right) +\frac{1}{2}\left$ 



#### MapReduce

# MapReduce Applications

An important early distributed processing system was MapReduce, developed at Google Generic application 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: The values for a key are processed as a sequence (reduce)

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

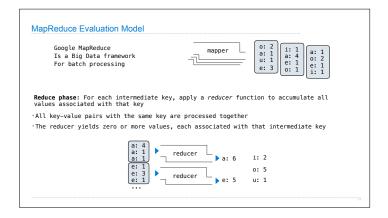
#### MapReduce Evaluation Model

Map phase: Apply a mapper function to all inputs, emitting intermediate key-value pairs · The mapper yields zero or more key-value pairs for each input



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

- All key-value pairs with the same key are processed together
- \*The reducer yields zero or more values, each associated with that intermediate key



Key-value pairs are jus	t two-element Py	thon 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 returne by calls to f
data.reduceByKey(fn)	Key-value pairs	Two values	One value	One key-value pair for each unique key
		(Demo)		