61A Lecture 35
Announcements
Unix
Computer Systems

Systems research enables application development by defining and implementing abstractions:
Computer Systems

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A unifying property of effective systems:
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A unifying property of effective systems:

> Hide complexity, but retain flexibility
Example: The Unix Operating System
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(Demo)

```
cd ww/assets/slides && ls *.pdf | cut -f 1 -d - | sort -r | uniq -c
```
Python Programs in a Unix Environment
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(Demo)
Big Data
Big Data Examples

Examples from Anthony Joseph
Big Data Examples

Facebook's daily logs: 60 Terabytes (60,000 Gigabytes)
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Typical hardware for big data applications:

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- Independent computers are stored in racks
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- When using many computers, some will fail!

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Apache Spark
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All of these operations can be performed on RDDs that are partitioned across machines
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**Romeo & Juliet**

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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,
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• A driver program defines transformations and actions on an RDD

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Apache Spark Interface

The Last Words of Shakespeare (Demo)

A SparkContext gives access to the cluster manager

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>>> x = sc.textFile('shakespeare.txt')
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```python
>>> x.sortBy(lambda s: s, False).take(2)
['you shall...', 'yet, a...']
```

--

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```python
>>> sc
< pyspark.context.SparkContext ... >
```

```python
>>> x = sc.textFile('shakespeare.txt')
```

```python
>>> x.sortBy(lambda s: s, False).take(2)
['you shall ...', 'yet , a ...']
```

King Lear

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 , naught could remove ,
Is now the two hours' traffic of our stage ;

The which if you with patient ears attend ,
What here shall miss , our toil shall strive to mend .

Romeo & Juliet

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Step 1: Each element in an input collection produces zero or more key-value pairs (map)
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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
MapReduce Evaluation Model

**Map phase:** Apply a *mapper* function to all inputs, emitting intermediate key-value pairs.
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Google MapReduce
Is a Big Data framework
For batch processing
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mapper

{o: 2,
a: 1,
u: 1,
e: 3}
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</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>1</td>
</tr>
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<tbody>
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<td>o</td>
<td>2</td>
</tr>
<tr>
<td>a</td>
<td>1</td>
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<tr>
<td>u</td>
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<td>i</td>
<td>1</td>
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<tr>
<td>a</td>
<td>4</td>
</tr>
<tr>
<td>e</td>
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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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```
a: 4
a: 1
a: 1
e: 1
e: 3
e: 1...
```
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Key-value pairs are just two-element Python tuples
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Key-value pairs are just two-element Python tuples

data.flatMap(fn)
MapReduce Applications on Apache Spark

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data.flatMap(fn)

data.reduceByKey(fn)
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Call Expression

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Call Expression \hspace{1cm} Data

dataflatMap(fn)

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```
Call Expression                  Data                  fn Input
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Call Expression: `flatMap` and `reduceByKey`.

Data: Values and Key-value pairs.

fn Input: One value and Two values.

fn Output: Zero or more key-value pairs and All key-value pairs returned by calls to fn.
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(Demo)