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CS61C

Great Ideas in Computer Architecture

(a.k.a. Machine Structures)

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MapReduce & Spark

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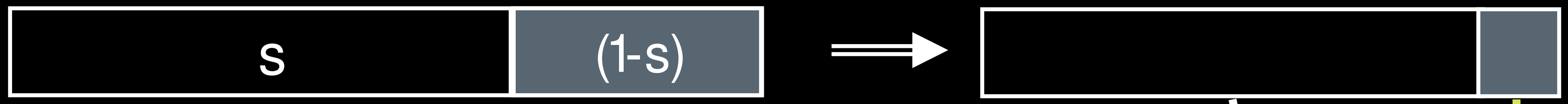
Amdahl’s Law

Amdahl's (Heartbreaking) Law

- Speedup due to enhancement E:

$$\text{Speedup w/E} = \frac{\text{Exec time w/o E}}{\text{Exec time w/E}}$$

- Example
  - Enhancement E does not affect a portion s (where s<1) of a task.
  - It does accelerate the remainder (1-s) by a factor P (P>1).



- Exec time w/E = Exec Time w/o E × [s + (1-s)/P]
- Speedup w/E = 1 / [s + (1-s)/P]

Amdahl's Law

- Speedup $= \dfrac{1}{s + \dfrac{(1-s)}{P}} \le \dfrac{1}{s}$ (as $P \rightarrow \infty$)

Non-sped-up part

Sped-up part

- Example: the execution time of 4/5 of the program can be accelerated by a factor of 16.
What is the program speed-up overall?

$$\frac{1}{0.2 + \frac{0.8}{16}} = \frac{1}{0.2 + 0.05} = \frac{1}{0.25} = 4$$

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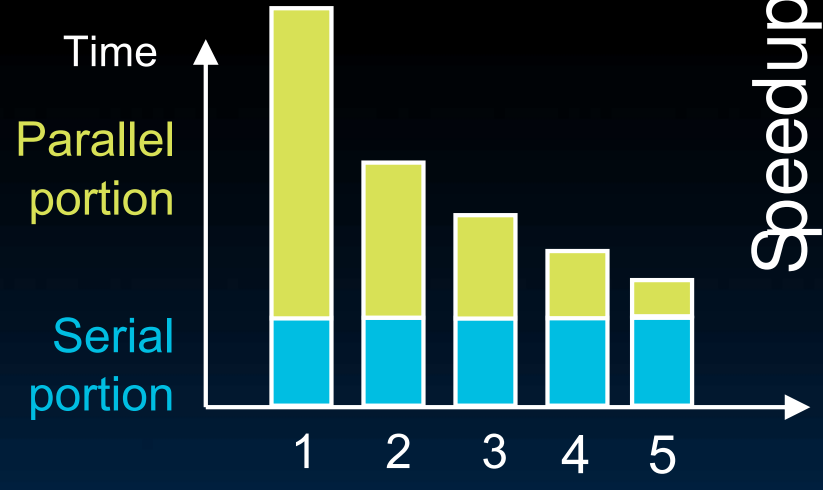
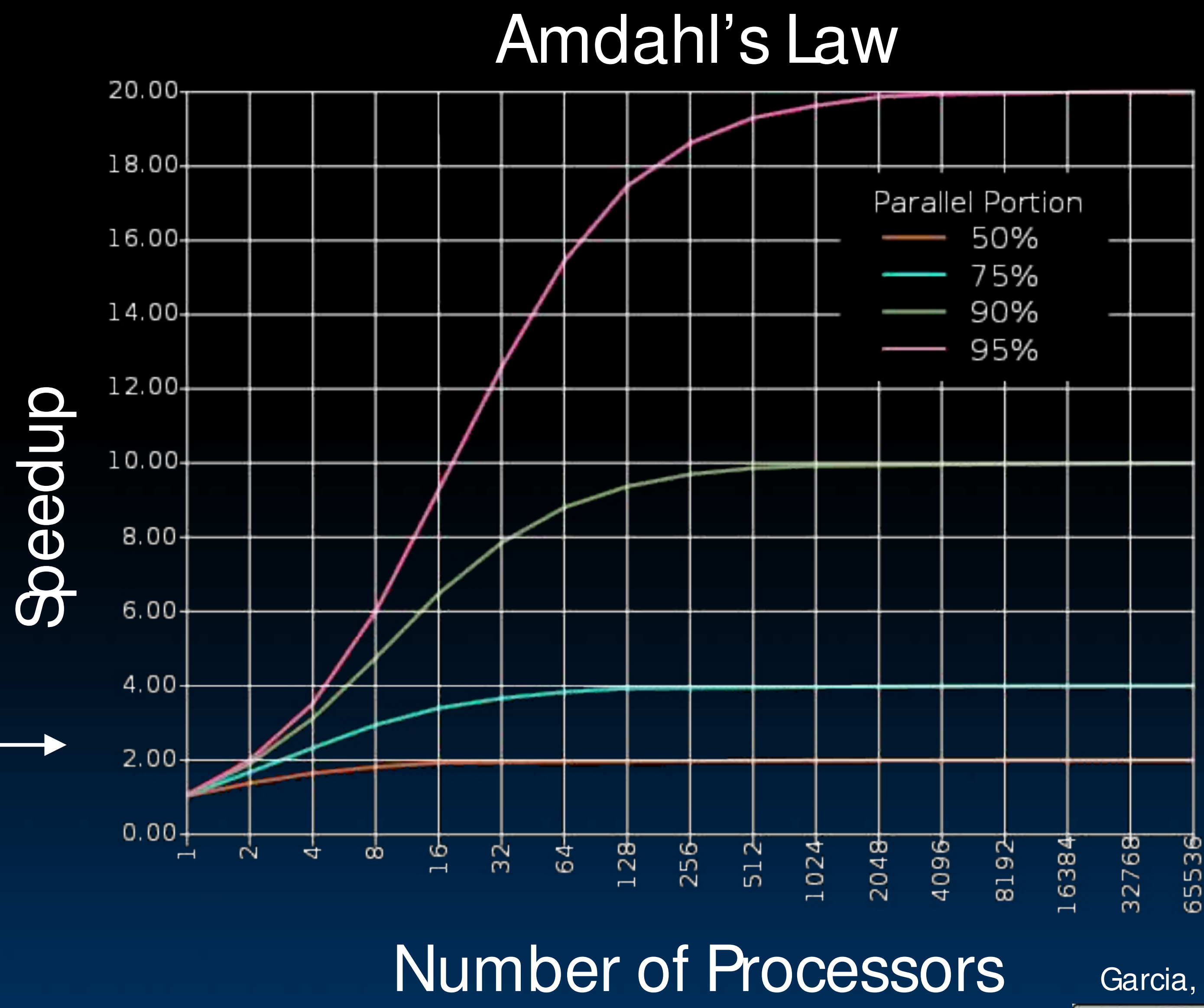
Consequence of Amdahl's Law

- The amount of speedup that can be achieved through parallelism is limited by the serial (s) portion of your program!
- Speedup ≤ 1/s





Request-Level and Data-Level Parallelism

New-School Machine Structures

Software

Parallel Requests
Assigned to computer
e.g., Search “Cats”

Parallel Threads
Assigned to core e.g., Lookup, Ads

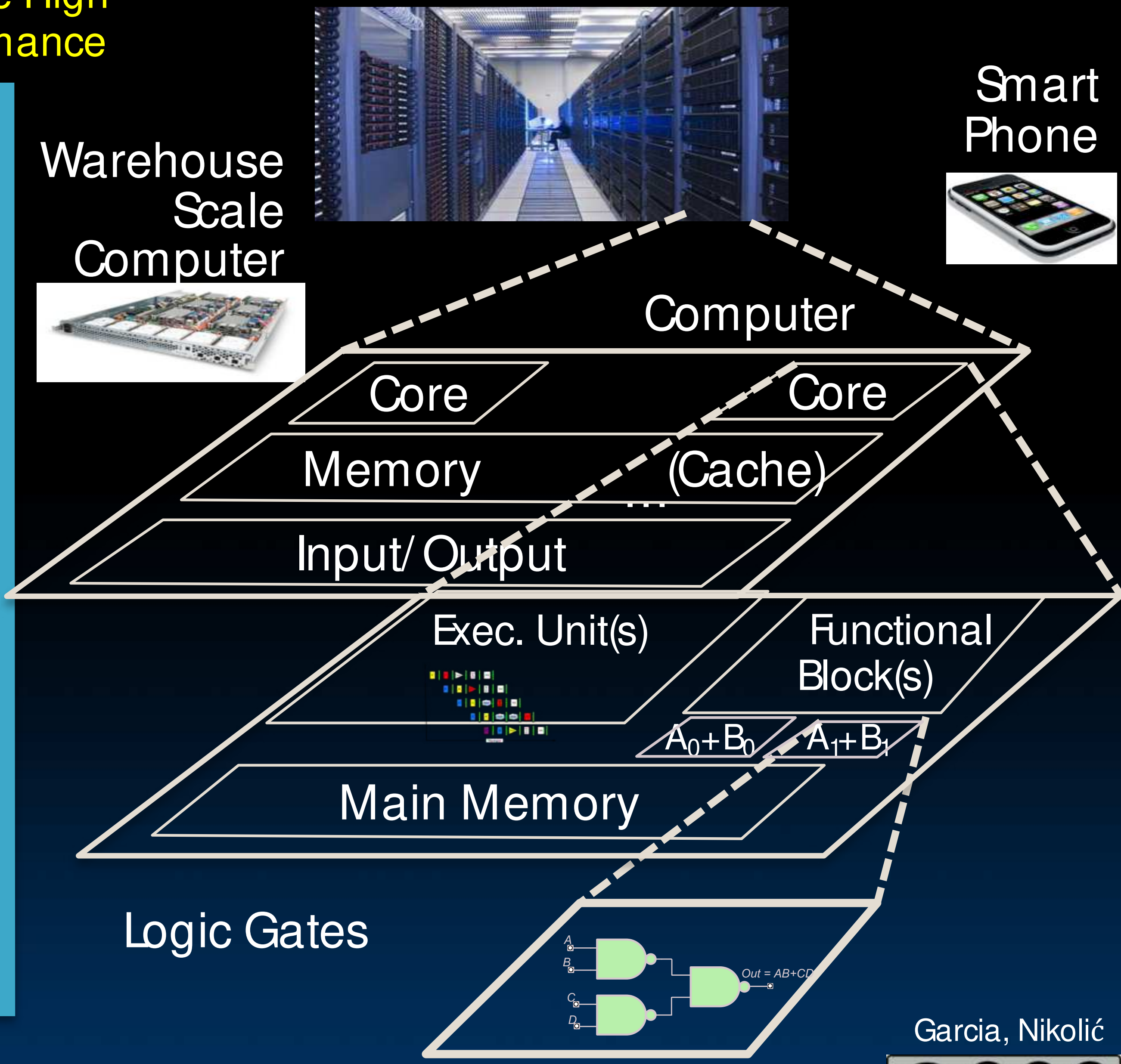
Parallel Instructions
>1 instruction @ one time
e.g., 5 pipelined instructions

Parallel Data
>1 data item @ one time
e.g., Add of 4 pairs of words

Hardware descriptions
All gates work in parallel at same time

Harness Parallelism & Achieve High Performance

Hardware



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Request-Level Parallelism (RLP)

- Hundreds or thousands of requests/ sec
  - Not your laptop or cell-phone, but popular Internet services like web search, social networking, …
  - Such requests are largely independent
    - Often involve read-mostly databases
    - Rarely involve strict read–write data sharing or synchronization across requests
- Computation easily partitioned within a request and across different requests

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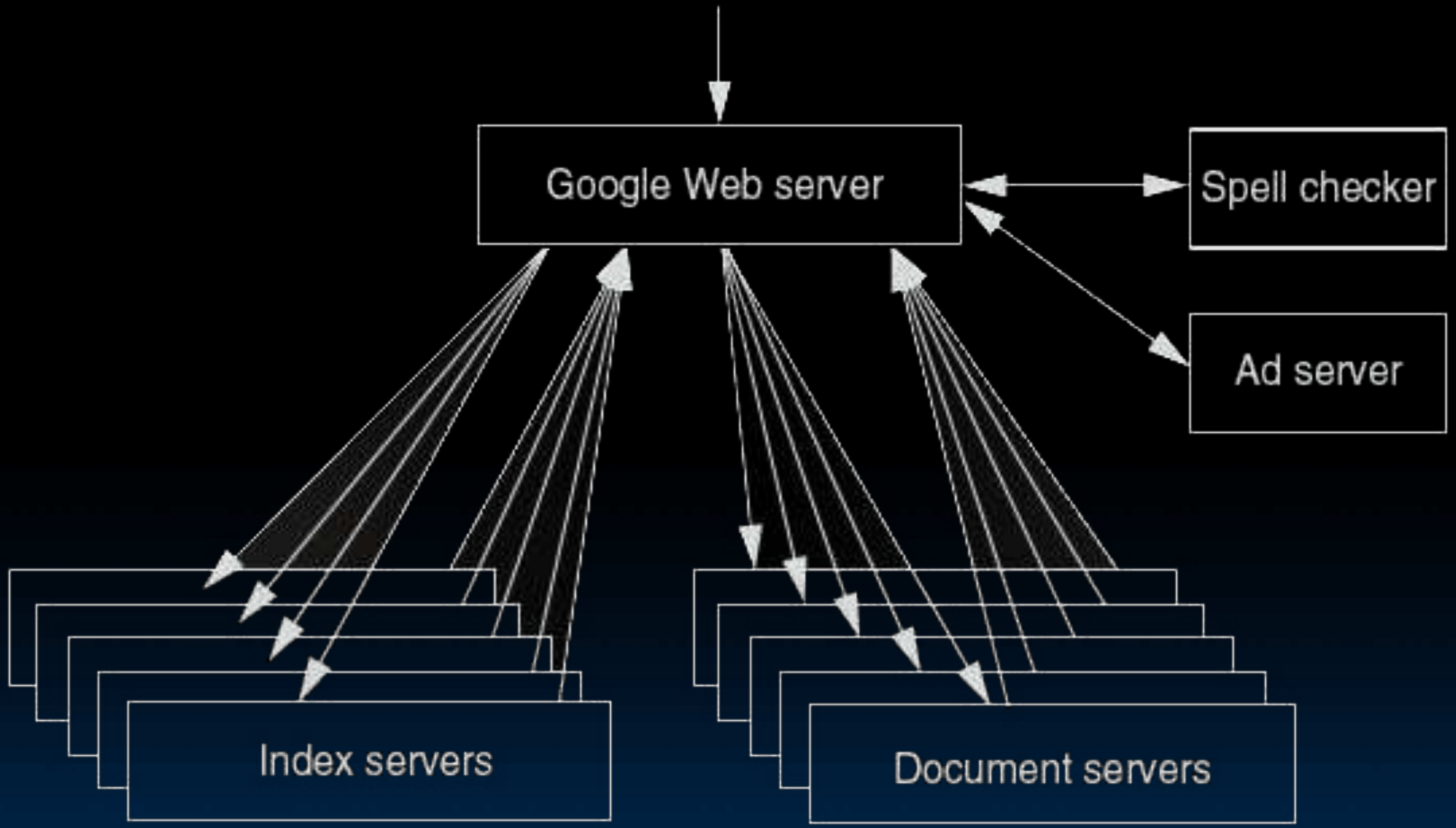
Google Query-Serving Architecture



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Data-Level Parallelism (DLP)

- Two kinds:
  - Lots of data in memory that can be operated on in parallel (e.g. adding together 2 arrays)
  - Lots of data on many disks that can be operated on in parallel (e.g. searching for documents)
- Today's lecture: DLP across many servers and disks using MapReduce

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MapReduce

What is MapReduce?

- Simple data-parallel programming model designed for scalability and fault-tolerance
- Pioneered by Google
  - Processes > 25 petabytes of data per day
- Open-source Hadoop project
  - Used at Yahoo!, Facebook, Amazon, …

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What is MapReduce used for?

- At Google:
  - Index construction for Google Search
  - Article clustering for Google News
  - Statistical machine translation
  - For computing multi-layer street maps
- At Yahoo!:
  - "Web map" powering Yahoo! Search
  - Spam detection for Yahoo! Mail
- At Facebook:
  - Data mining
  - Ad optimization
  - Spam detection

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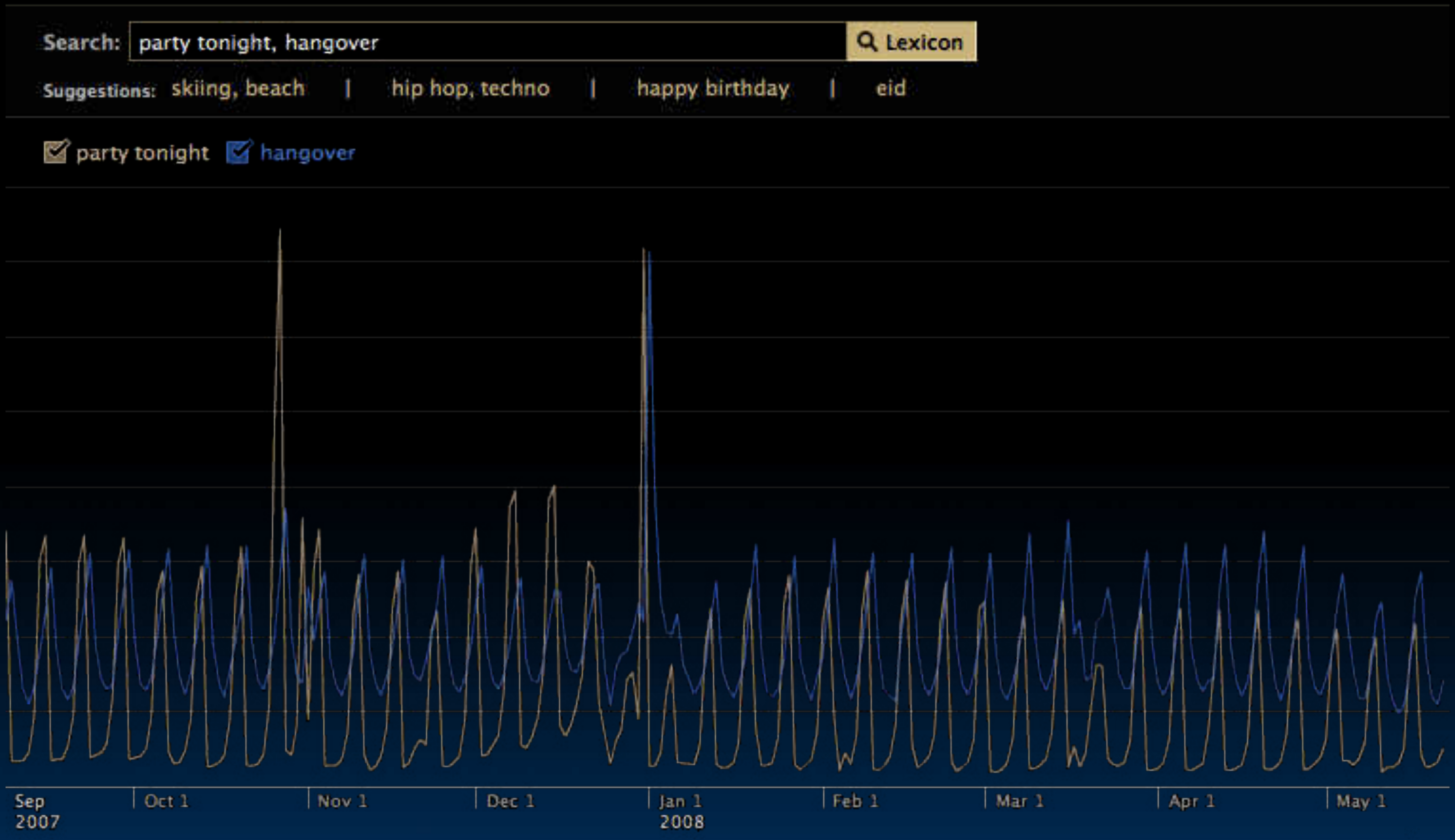
Example: Facebook Lexicon



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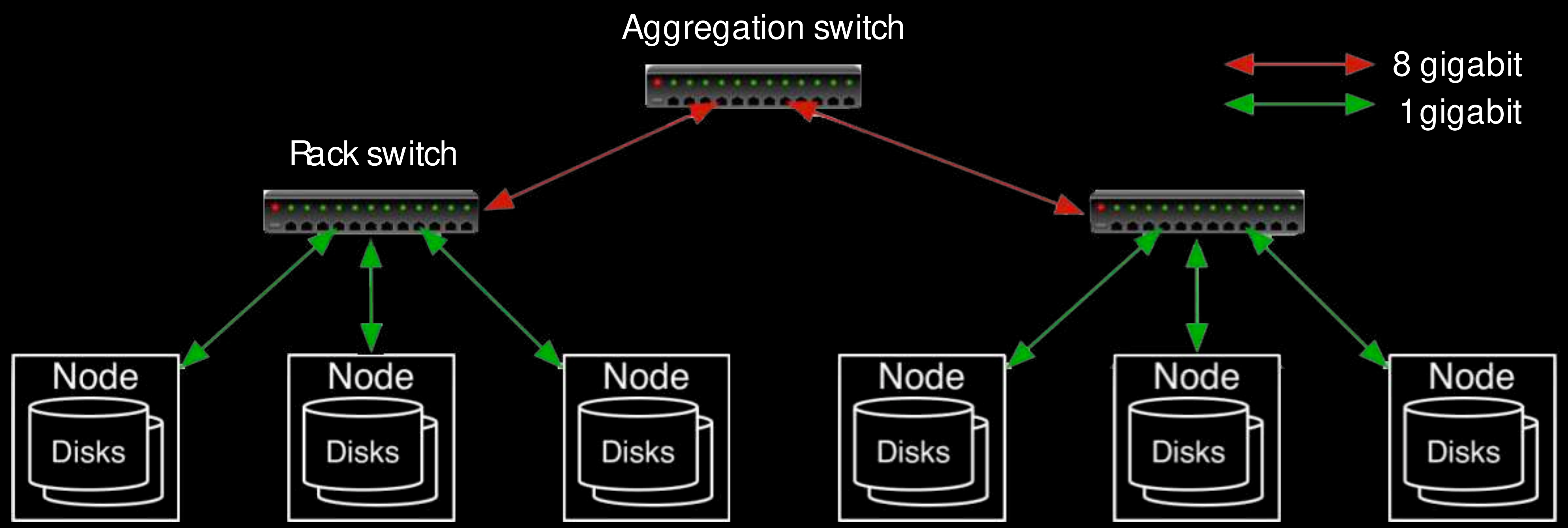
MapReduce Design Goals

- Scalability to large data volumes:
  - 1000's of machines, 10,000's of disks
- Cost-efficiency:
  - Commodity machines (cheap, but unreliable)
  - Commodity network
  - Automatic fault-tolerance via re-execution (fewer administrators)
  - Easy, fun to use (fewer programmers)
- Jeffrey Dean and Sanjay Ghemawat, "MapReduce: Simplified Data Processing on Large Clusters," 6th USENIX Symposium on Operating Systems Design and Implementation, 2004.
  - optional reading, linked on course homepage – a digestible CS paper at the 61C level

Typical Hadoop Cluster

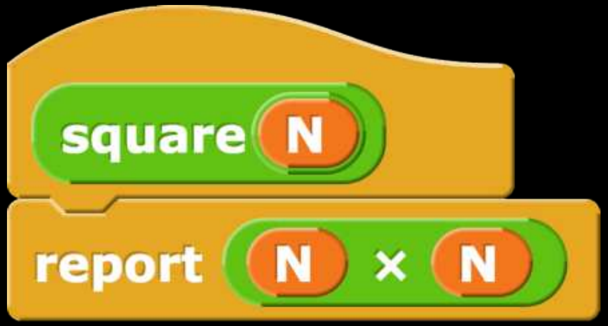


- 40 nodes/rack, 1000-4000 nodes in cluster
- 1 Gbps bandwidth within rack, 8 Gbps out of rack
- Node specs (Yahoo terasort):
  8 x 2GHz cores, 8 GB RAM, 4 disks (= 4 TB?)

Image from http://wiki.apache.org/hadoop-data/attachments/HadoopPresentations/attachments/YahooHadoopIntro-apachecon-us-2008.pdf

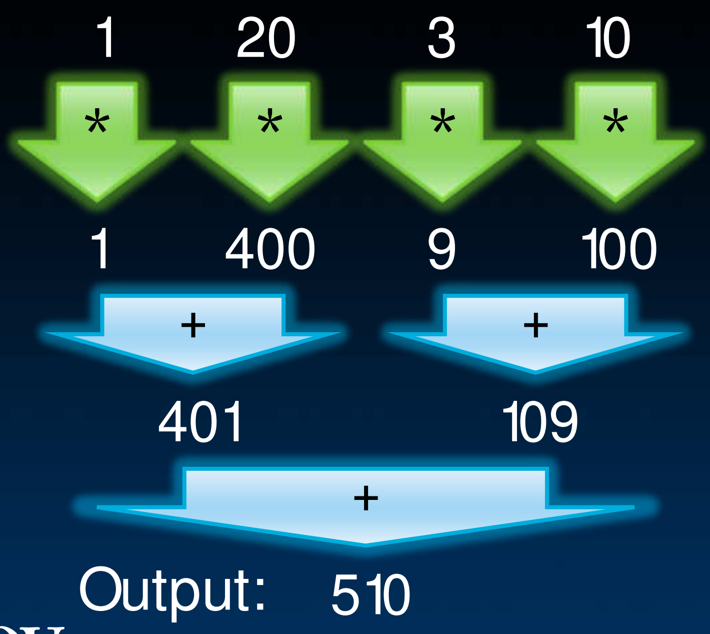
MapReduce in CS10 & CS61A{,S}

en.wikipedia.org/wiki/MapReduce




```
> (reduce +
    (map square '(1 20 3 10))
510
```

Input:



Note: only two data types!

```
>>> from functools import reduce
>>> def plus(x,y): return x+y
>>> def square(x): return x*x
>>> reduce(plus,
        map(square, (1,20,3,10)))
510
```

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MapReduce Programming Model

Input & Output: each a set of key/value pairs

Programmer specifies two functions:

```
map (in_key, in_value) →
      list(interm_key, interm_value)
```

- Processes input key/value pair
- Slices data into "shards" or "splits"; distributed to workers
- Produces set of intermediate pairs

```
reduce (interm_key, list(interm_value)) →
         list(out_value)
```

- Combines all intermediate values for a particular key
- Produces a set of merged output values (usu just one)

code.google.com/edu/parallel/mapreduce-tutorial.html

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MapReduce WordCount Example

- "Mapper" nodes are responsible for the **map** function

```
// "I do I learn" → ("I",1), ("do",1), ("I",1), ("learn",1)
map(String input_key,
    String input_value):
    // input_key  : document name (or line of text)
    // input_value: document contents
    for each word w in input_value:
        EmitIntermediate(w, "1");
```

- "Reducer" nodes are responsible for the **reduce** function

```
// ("I",[1,1]) → ("I",2)
reduce(String output_key,
       Iterator intermediate_values):
    // output_key    : a word
    // output_values: a list of counts
    int result = 0;
    for each v in intermediate_values:
        result += ParseInt(v);
    Emit(AsString(result));
```

- Data on a distributed file system (DFS)

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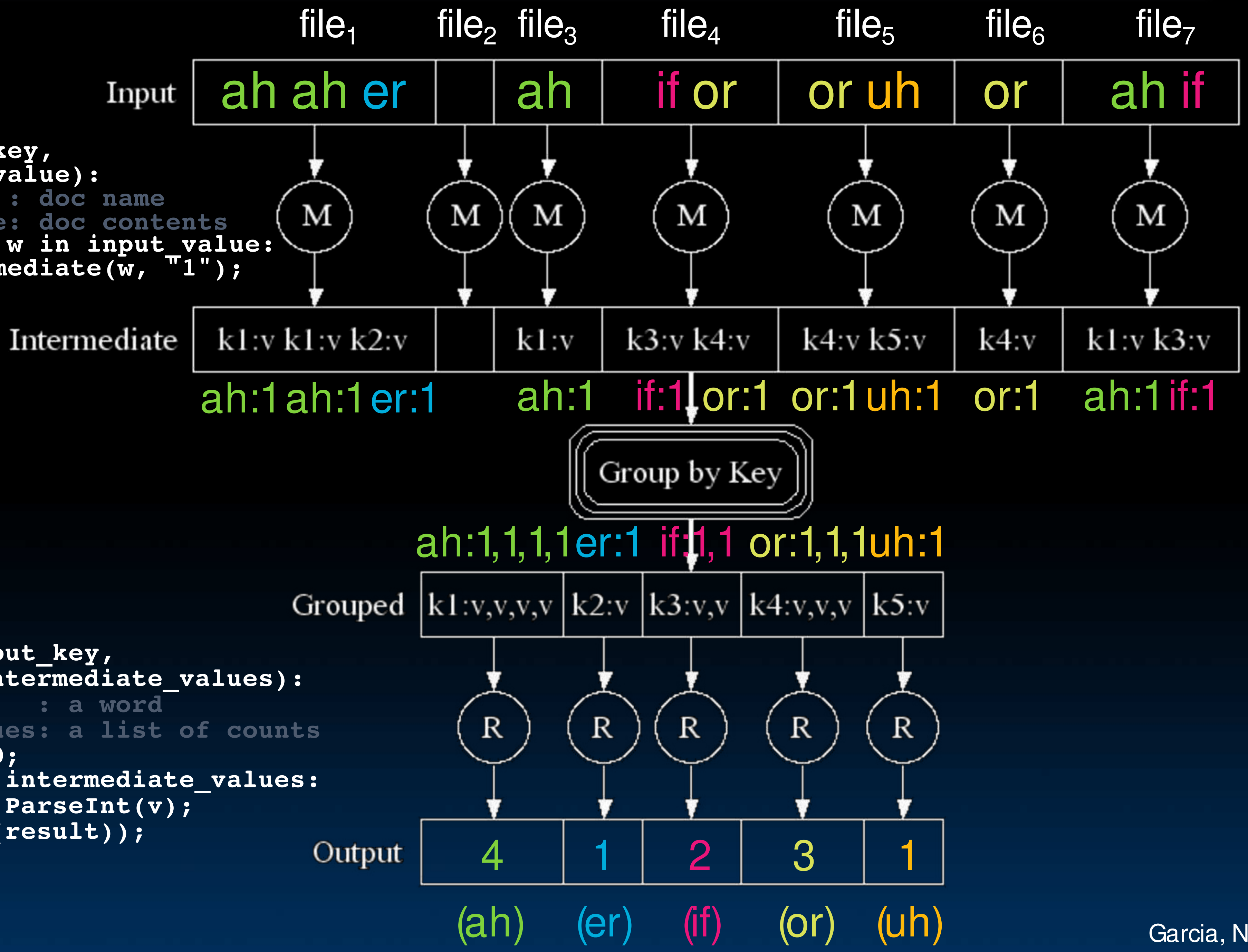
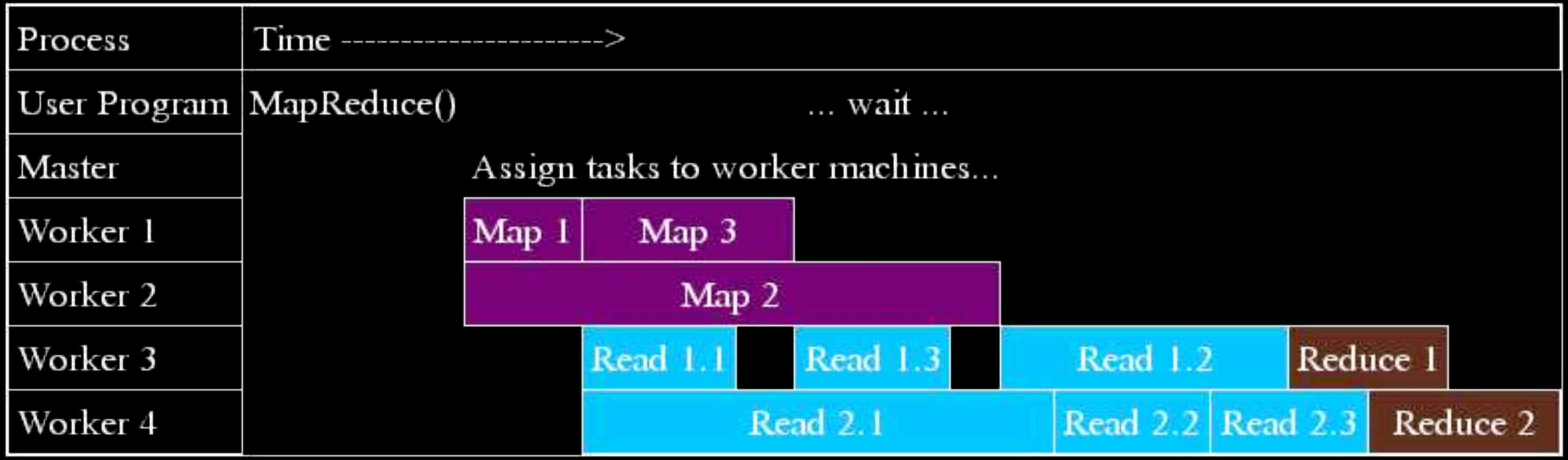
MapReduce WordCount Diagram

```
map(String input_key,
    String input_value):
    // input_key   : doc name
    // input_value: doc contents
    for each word w in input_value:
        EmitIntermediate(w, "1");
```




```
reduce(String output_key,
       Iterator intermediate_values):
    // output_key    : a word
    // output_values: a list of counts
    int result = 0;
    for each v in intermediate_values:
        result += ParseInt(v);
    Emit(AsString(result));
```

MapReduce Processing Time Line



- Master assigns map + reduce tasks to “worker” servers
- As soon as a map task finishes, worker server can be assigned a new map or reduce task
- Data shuffle begins as soon as a given Map finishes
- Reduce task begins as soon as all data shuffles finish
- To tolerate faults, reassign task if a worker server “dies”

MapReduce WordCount Java code

```java
public static void main(String[] args) throws IOException {
    JobConf conf = new JobConf(WordCount.class);
    conf.setJobName("wordcount");
    conf.setOutputKeyClass(Text.class);
    conf.setOutputValueClass(IntWritable.class);
    conf.setMapperClass(WCMap.class);
    conf.setCombinerClass(WCReduce.class);
    conf.setReducerClass(WCReduce.class);
    conf.setInputPath(new Path(args[0]));
    conf.setOutputPath(new Path(args[1]));
    JobClient.runJob(conf);
}

public class WCMap extends MapReduceBase implements Mapper {
    private static final IntWritable ONE = new IntWritable(1);
    public void map(WritableComparable key, Writable value,
                    OutputCollector output,
                    Reporter reporter) throws IOException {
        StringTokenizer itr = new StringTokenizer(value.toString());
        while (itr.hasMoreTokens()) {
            output.collect(new Text(itr.next()), ONE);
        }
    }
}

public class WCReduce extends MapReduceBase implements Reducer {
    public void reduce(WritableComparable key, Iterator values,
                       OutputCollector output,
                       Reporter reporter) throws IOException {
        int sum = 0;
        while (values.hasNext()) {
            sum += ((IntWritable) values.next()).get();
        }
        output.collect(key, new IntWritable(sum));
    }
}
```

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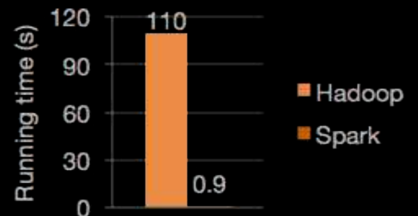
Spark

Spark

- Apache Spark™ is a fast and general engine for large-scale data processing.



- Speed
  - Run programs up to 100x faster than Hadoop MapReduce in memory, or 10x faster on disk.
  - Spark has an advanced DAG execution engine that supports cyclic data flow and in-memory computing.
- Ease of Use
  - Write applications quickly in Java, Scala or Python.
  - Spark offers over 80 high-level operators that make it easy to build parallel apps. And you can use it *interactively* from the Scala and Python shells.

Word Count in Spark's Python API

```python
file.flatMap(lambda line: line.split())
    .map(lambda word: (word, 1))
    .reduceByKey(lambda a, b: a+b)
```

Cf Java:

```java
public static void main(String[] args) throws IOException {
    JobConf conf = new JobConf(WordCount.class);
    conf.setJobName("wordcount");
    conf.setOutputKeyClass(Text.class);
    conf.setOutputValueClass(IntWritable.class);
    conf.setMapperClass(WCMap.class);
    conf.setCombinerClass(WCReduce.class);
    conf.setReducerClass(WCReduce.class);
    conf.setInputPath(new Path(args[0]));
    conf.setOutputPath(new Path(args[1]));
    JobClient.runJob(conf);
}

public class WCMap extends MapReduceBase implements Mapper {
    private static final IntWritable ONE = new IntWritable(1);
    public void map(WritableComparable key, Writable value,
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        StringTokenizer itr = new StringTokenizer(value.toString());
        while (itr.hasMoreTokens()) {
            output.collect(new Text(itr.next()), ONE);
        }
    }
}

public class WCReduce extends MapReduceBase implements Reducer {
    public void reduce(WritableComparable key, Iterator values,
                       OutputCollector output,
                       Reporter reporter) throws IOException {
        int sum = 0;
        while (values.hasNext()) {
            sum += ((IntWritable) values.next()).get();
        }
        output.collect(key, new IntWritable(sum));
    }
}
```

flatMap in Spark's Python API

```
>>> def neighbor(n):
...     return [n-1,n,n+1]
>>> R = sc.parallelize(range(5))
>>> R.collect()
[0, 1, 2, 3, 4]
>>> R.map(neighbor).collect()
[[-1, 0, 1], [0, 1, 2], [1, 2,
3], [2, 3, 4], [3, 4, 5]]
>>> R.flatMap(neighbor).collect()
[-1, 0, 1, 0, 1, 2, 1, 2, 3, 2,
3, 4, 3, 4, 5]
```

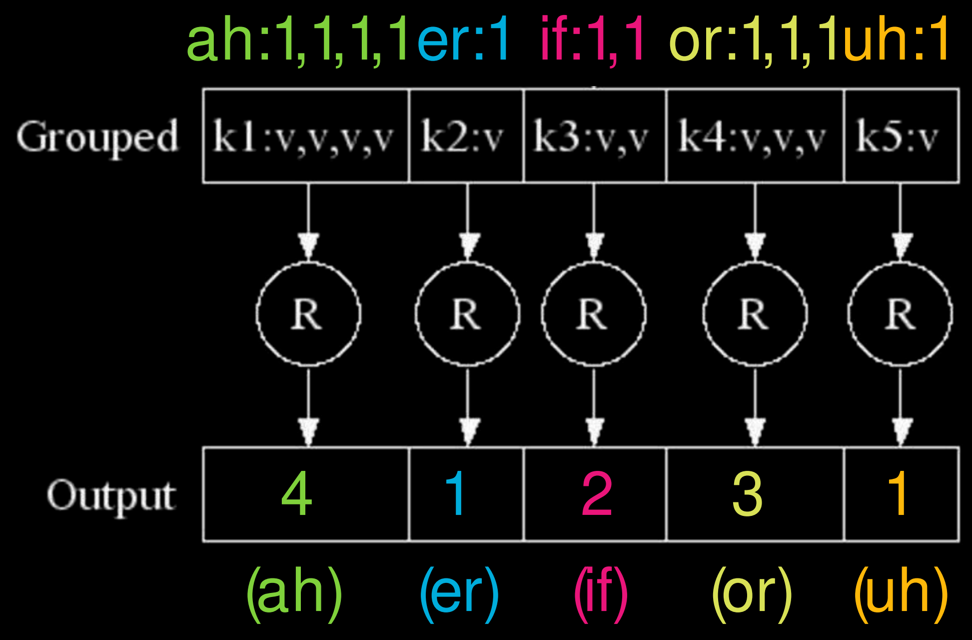
Word Count in Spark's Python API

```
unix% cat file.txt
ah ah er

ah
if or
or uh
or
ah if

>>> W = sc.textFile("file.txt")

>>> W.flatMap(lambda line: line.split()).collect()
['ah', 'ah', 'er', 'ah', 'if', 'or', 'or', 'uh', 'or', 'ah', 'if']
>>> W.flatMap(lambda line: line.split()).map(lambda word:
(word,1)).collect()
[('ah', 1), ('ah', 1), ('er', 1), ('ah', 1), ('if', 1), ('or', 1),
('or', 1), ('uh', 1), ('or', 1), ('ah', 1), ('if', 1)]
>>> W.flatMap(lambda line: line.split()).map(lambda word:
(word,1)).reduceByKey(lambda a,b: a+b).collect()
[('er', 1), ('ah', 4), ('if', 2), ('or', 3), ('uh', 1)]
```



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Parallel? Let's sanity-check…

```
>>> def crunch(n):
...     time.sleep(5) ## to simulate number crunching
...     return n*n
...
>>> crunch(10) ## 5 seconds later
100
>>> list(map(crunch,range(4))) ## 20 seconds later
[0, 1, 4, 9]
>>> R = sc.parallelize(range(4))
>>> R.map(crunch).collect() ## 5 seconds later
[0, 1, 4, 9]
```


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Conclusion

- 4th big idea is parallelism
- Amdahl's Law constrains performance wins
  - With infinite parallelism, Speedup = 1/s (s=serial %)
- MapReduce is a wonderful abstraction for programming thousands of machines
  - Hides details of machine failures, slow machines
  - File-based
- Spark does it even better
  - Memory-based
  - Lazy evaluation

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