





# Distributed Computing Lesson 23: MapReduce with Hadoop

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## **Outline**



- MapReduce & Hadoop
- 2 Examples



## **Overview**



- What is MapReduce?
- Distinguish use cases of Hadoop/MapReduce, MPI, Servlets
- Getting to know the MapReduce support of the Hadoop framework

## HTTP/Web Services/Java Servlet Use Case



HTTP, Web Services, and Java Servlets are ideal for



Applications with request-response and client-server scheme



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- Data processing does not take place in a natural distributed fashion
- Requests are answered by single threads, cooperative parallelism does not improve overall performance
- We want to combine different applications in a heterogeneous system



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- Size of data that needs to be transmitted is smaller in comparison to runtime of computations (see point 1).
- We are in a scientific environment and do not need to connect to other software such as enterprise systems.



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Distributed Computing



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- Our data comes from and results need to be passed to other applications, such as enterprise systems, which may use stacks such as HTTP/Java Servlet/Web Service.



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- large-scale parallel image processing

# MapReduce with Hadoop



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- MapReduce is a programming model and an associated implementation for processing and generating large data sets with a parallel, distributed algorithm on a cluster. [4]
- Conceptually similar to scatter/reduce in MPI

# Divide & Conquer



 Data is divided into smaller pieces, each piece corresponds to a problem part. The parts are solved separately and the separate solutions are combined to final results.

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# Divide & Conquer



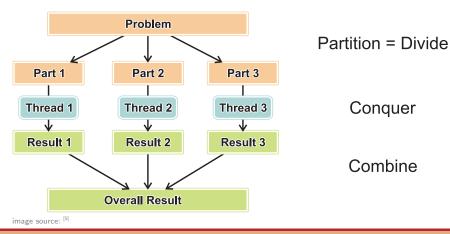
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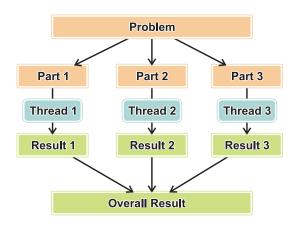
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# MapReduce



• solving of partial problems = mapping; combination of partial results to final results = reduce



Partition = Divide

**Mapping** 

Reducing

## Hadoop



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- Due to time restrictions, we will only consider the MapReduce part



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- We can also do this locally on each node, after Map and before Reduce, to reduce the amount of communication needed (this is called combination)

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<Text (the word), WriteableInteger (always value 1)>, where the WriteableInteger is stands for the number of appearences



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- If a word occurs multiple times in a line, one token is emitted for each occurrence.



## Listing: The mapper class.

```
package wordCount;
public class WordCountMapper
    extends Mapper < LongWritable, Text, Text, IntWritable > {
 public static final IntWritable ONE = new IntWritable(1);
  @Override
  protected void map(final LongWritable offset, final Text line,
      final Context context) throws IOException, InterruptedException {
   for (String word : line.toString() // replace punctuation and other
        .replace('.', 'u').replace(',', 'u').replace('/', 'u')// strange
        .replace(']', 'u').replace('[', 'u').replace('_', 'u')// chars
        .replace(')', '||').replace('(', '||').replace('#', '||')// with
        .replace('!', '"').replace('?', '"').replace("-", "")// spaces
        .replace("\"", "").replace("\'", "").replaceAll("[0-9]+", """)//
        .replace(':', ''').replace('\t', ''').replace('\f', ''')//
        .split("\\s+")) {// iterate over all space-separated words
      word = word.trim():
      if (word.length() > 0) {// emit one tuple <WORD, 1> for each WORD
        context.write(new Text(word.toLowerCase()), WordCountMapper.ONE);
```



• After this mapping step, the reducer is applied.

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<Text (the word), Iterable<WriteableInteger> (number of occurrences)>
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Hadoop has put all the <writeableInteger> for the same
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 The reducer can also be used as combinator: Before sending the results of the mapper to the central reducer, we can add up the tuples (WriteableInteger s) for the same key (word, Text).



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 The reducer can also be used as combinator: Before sending the results of the mapper to the central reducer, we can add up the tuples (WriteableInteger s) for the same key (word, Text). This way we reduce the data volume.

```
package wordCount;
public class WordCountReducer
    extends Reducer < Text, IntWritable, Text,
       IntWritable> {
  Olverride
  protected void reduce(final Text key, final
     Iterable < IntWritable > values,
      final Context context) throws IOException,
         InterruptedException {
    // we receive tuples of the type <WORD,
       IntWritable> for each WORD
    int count = 0;
    for (final IntWritable current : values) { //
       we add up all the ints
      count += current.get();
    }
    context.write(key, new IntWritable(count));//
       and emit the final count
```

### **WordCount Driver**



• We put everything together in a "driver" class

#### **Driver Class**



#### Listing: The driver class.

```
package wordCount:
public class WordCountDriver extends Configured implements Tool {
 public static void main(final String[] args) throws Exception {
   System.exit(ToolRunner.run(new Configuration(), //
        new WordCountDriver(), args));
 Offverride
 public int run(final String[] args) throws Exception {
   final Configuration conf:
   final Job job;
    conf = new Configuration():
   job = Job.getInstance(conf, "Word, Count, Map-Reduce");
   iob.setJarBvClass(WordCountDriver.class):
   if (args.length < 2) {
     return 1:
   job.setMapperClass(WordCountMapper.class); // set mapper
   iob.setReducerClass(WordCountReducer.class):// set reducer
   iob.setCombinerClass(WordCountReducer.class):// set combiner
    job.setOutputKeyClass(Text.class); // set output key class
   iob.setOutputValueClass(IntWritable.class): // set output value class
    job.setInputFormatClass(TextInputFormat.class); // set input format
   iob.setOutputFormatClass(TextOutputFormat.class): // set output format
    FileInputFormat.setInputPaths(job, new Path(args[0]));
    FileOutputFormat.setOutputPath(iob. new Path(args[1])):
   job.waitForCompletion(true);
   return 0:
```

## **Maven Setup**



• We can set up this project by using Maven

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# Maven Setup



- We can set up this project by using Maven
- And create an executable jar with mvn clean compile package



#### Listing: [pom.xml] - Part 1: Basic Project Information



#### Listing: [pom.xml] - Part 2: Information about Organization

```
<url>http://www.it-weise.de/</url>
<organization>
  <url>http://www.it-weise.de/</url>
  <name>thomasWeise</name>
</organization>
```



#### Listing: [pom.xml] - Part 3: Information about Developer

```
<developers>
  <developer>
    <id>thomasWeise</id>
    <name>Thomas Weise</name>
    <email>tweise@ustc.edu.cn</email>
    <url>http://www.it-weise.de/</url>
    <organization>University of Science and Technology of
       China (USTC) </organization>
    <organizationUrl>http://www.ustc.edu.cn/</organizationUrl>
    <roles>
      <role>architect</role>
      <role>developer</role>
    </roles>
    <timezone>China Time Zone</timezone>
  </developer>
</developers>
```



#### Listing: [pom.xml] - Part 4: Properties for Rest of pom



### Listing: [pom.xml] - Part 5: Licensing



#### Listing: [pom.xml] - Part 6: SCM, Issue Management, and Inception Year



### Listing: [pom.xml] - Part 7: Dependencies

### pom.xml



### Listing: [pom.xml] - Part 8: Build

```
<finalName>wordCount</finalName>
<plugine>
  <plugin>
    (groupId)org.apache.maven.pluging(/groupId)
    <artifactId>maven-compiler-plugin</artifactId>
    (configuration)
      <source>$(jdk.version)</source>
      <target>$(jdk.vermion)</target>
      <encoding>$(encoding)</encoding>
      <showWarnings>true</showWarnings>
      <showDeprecation>true</showDeprecation>
    </configuration>
  </plugin>
    <groupId>org.apache.maven.plugins</groupId>
    <artifactId>maren-shade-plugip</artifactId>
    <executions>
      <execution>
        <phage>package</phage>
        (goals)
          <goal>shade</goal>
        </goals>
        (configuration)
          <mininizeJar>false</mininizeJar>
          (shadedArtifactAttached)true(/shadedArtifactAttached)
          <createDependencyReducedPom>false</createDependencyReducedPom>
          <finalName>wordCount-full</finalName>
          <filters>
              <artifact>*:*</artifact>
              <excludes>
               <exclude>META-INF/*.SF</exclude>
<exclude>META-INF/*.DSA</exclude>
                <exclude>META-INF/*.RSA</exclude>
              </excludes>
          </filters>
          (transformers)
            <transformer</pre>
              implementation="org.apache.maven.plugins.shade.resource.ManifestResourceTransformer">
              <mainClass>$(project.mainClass)</mainClass>
              implementation="org.apache.mayen.pluging.ghade.resource.ApachelicengeResourceTransformer" />
              implementation="org.apache.maven.plugins.shade.resource.ApacheNoticeResourceTransformer" />
              implementation="org.apache.maven.plugins.shade.resource.PluginXnlResourceTransformer" />
              implementation="org.apache.maven.plugins.shade.resource.ServicesResourceTransformer" />
  </plugia>
</plugina>
```

</build>



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- Enter the hadoop folder and perform the following steps:
  - bin/hdfs namenode -format



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  - bin/hdfs namenode -format
  - sbin/start-dfs.sh



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  - bin/hdfs namenode -format
  - sbin/start-dfs.sh
  - 6 bin/hdfs dfs -mkdir /user



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• Try to find the interconnection between pages

Distributed Computing



- Try to find the interconnection between pages
- Input to Mapper: List of URLs (as Text s)

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- Output of Reducer: List of URLs to shared resources and URLs (from Mapper input) referencing them



- Try to find the interconnection between pages
- Input to Mapper: List of URLs (as Text s)
- Output of Mapper: Tuples of URL to resources and URLs from input referencing them
- Input of Reducer: Tuples of URL to a resources and *list* of URLs (from Mapper input) referencing them
- Output of Reducer: List of URLs to shared resources and URLs (from Mapper input) referencing them
- Having this, we can find out which resources are fundamental in the web, which are shared between different pages, and how the most important pages in China are interconnected

Distributed Computing



• The input of the MapReduce process are text files



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Distributed Computing



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- We emit all tuples <B as Text, A as Text>
- The process is applied recursively (up to a maximum depth)
- So we have tuples of resources and the URLs referencing them

```
package webFinder:
 * resources that are loaded by a given website URL and emits tuples of
public class WebFinderMapper
    extends Mapper < Long Writable, Text, Text, Text > {
 private static Logger LOGGER = Logger.getLogger(WebFinderMapper.class);
  @Override
  protected void map(final LongWritable offset, final Text line,
     final Context context) throws IOException, InterruptedException {
    final URL baseUrl:
    final URI baseUri;
    final int maxDepth:
    final Text baseUrlText:
    final HashSet < URL > done:
    String str;
    str = WebFinderMapper.__prepare(line.toString(), true);
    if (str == null) {// prepare base url
     return:
    maxDepth = context.getConfiguration().getInt("maxDepth", 1);
    baseUri = URI.create(str).normalize();
    baseUrl = baseUri.toURL():
    done = new HashSet <> (); // URLs that have been processed
    done.add(baseUrl):
```

#### Web Finder Reducer



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- The input of the Reducer are tuples of resources and lists of URLs referencing them
- For each resource URL, we compute the set of unique URLs referencing them
- If the set contains more then one resource, we have a resource shared among multiple of the originally provided URLs
- We will only output such elements, as tuple
   VRL, list of URLs referencing it>

```
package webFinder;
* f@code <resource URL. list of website urls>}.
public class WebFinderReducer
    extends Reducer < Text, Text, Text, List < Text>> {
  * f@code <resource URL, iterable of referencing website URLs>}, select
 @Override
 protected void reduce(final Text key, final Iterable < Text > values,
      final Context context) throws IOException, InterruptedException {
   final HashSet <URL> set;
   final int size:
    final ArravList list:
   String string;
   URL add;
    int index:
    set = new HashSet <>():
    looper: for (final Text url : values) {
      string = url.toString(); // convert value to a URL
     try {
       add = new URI(string).normalize().toURL():
     } catch (@SuppressWarnings("unused") final Throwable error) {
        trv f
         add = new URL(string).toURI().normalize().toURL();
       } catch (@SuppressWarnings("unused") final Throwable error2) {
         try {
            add = new URL(string):
         } catch (@SuppressWarnings("unused") final Throwable error3) {
           continue looper;
      set.add(add): // store value in set of URLs pointing to this resource
```

#### WebFinder Driver



• We put everything together in a "driver" class

#### The Driver Class



#### Listing: The driver class.

```
package webFinder;
public class WebFinderDriver extends Configured implements Tool {
 public static void main(final String[] args) throws Exception {
   try {
     final int res = ToolRunner.run(new Configuration(),
         new WebFinderDriver(), args);
      System.exit(res);
   } catch (final Exception e) {
      e.printStackTrace();
      System.exit(255);
 @Override
 public int run(final String[] args) throws Exception {
   final Configuration conf:
   final Job job:
   conf = new Configuration():
   job = Job.getInstance(conf, "WebFinder, MapReduce");
   job.setJarByClass(WebFinderDriver.class); // use current jar
   if (args.length < 2) {
     return 1;
   if (args.length > 2) {// set max depth and pass parameter to mapper
      conf.setInt("maxDepth", Integer.parseInt(args[2]));
   iob.setMapperClass(WebFinderMapper.class):// set mapper
   job.setMapOutputKeyClass(Text.class); // set mapper output key type
   job.setMapOutputValueClass(Text.class); // set mapper output value type
   iob.setReducerClass(WebFinderReducer.class):// set reducer
   job.setOutputKeyClass(Text.class); // set reducer output key type
   job.setOutputValueClass(List.class): // set reducer output value
   job.setInputFormatClass(TextInputFormat.class); // set input format
   job.setOutputFormatClass(TextOutputFormat.class); // set output format
   FileInputFormat.setInputPaths(iob. new Path(args[0])):
   FileOutputFormat.setOutputPath(job, new Path(args[1]));
```



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Distributed Computing



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Distributed Computing



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#### Listing: Output

```
http://c.vouku.com/ahoutcn/voutu [http://www.tudou.com. http://www.vouku.com]
http://c.vouku.com/abouteg/vouku [http://www.tudou.com. http://www.vouku.com]
http://c.youku.com/abouteg/youtu [http://www.tudou.com, http://www.youku.com]
http://cbjs.baidu.com/js/m.js [http://www.baidu.com, http://www.qq.com]
http://css.tudouui.com/skin/__g/img/sprite.gif [http://www.tudou.com, http://www.youku.com]
http://events.youku.com/global/scripts/jquery-1.8.3.js [http://www.tudou.com, http://www.youku.com]
http://events.vouku.com/global/scripts/vouku.js [http://www.tudou.com. http://www.vouku.com]
http://images.china.cn/images1/ch/appxz/2.ipg [http://www.gg.com. http://www.vouku.com]
http://images.china.cn/images1/ch/appxz/3.jpg [http://www.gg.com. http://www.vouku.com]
http://js.tudouui.com/v3/dist/js/lib_6.js [http://www.tudou.com, http://www.youku.com]
http://mail.qq.com [http://www.baidu.com, http://www.qq.com]
http://minisite.vouku.com/mini.common/urchin.is.[http://www.tudou.com. http://www.vouku.com]
http://plaver.vouku.com/jsapi [http://www.tudou.com. http://www.vouku.com]
http://gzone.gg.com [http://www.baidu.com. http://www.gg.com]
http://res.mfs.vkimg.com/051000004D92DF6197927339BA04E210.is [http://www.tudou.com. http://www.vouku.com]
http://static.youku.com/user/img/avatar/80/5.jpg [http://www.tudou.com, http://www.youku.com]
http://static.youku.com/user/img/avatar/80/9.jpg [http://www.tudou.com, http://www.youku.com]
http://weibo.com [http://www.baidu.com, http://www.qq.com]
http://www.12377.cn [http://www.baidu.com. http://www.gg.com. http://www.vouku.com]
http://www.12377.cn/node_548446.htm [http://www.qq.com, http://www.youku.com]
http://www.bijubao.org [http://www.baidu.com. http://www.vouku.com]
http://www.china.com.cn/player/video.js [http://www.qq.com, http://www.youku.com]
http://www.ellechina.com [http://www.qq.com, http://www.youku.com]
http://www.hao123.com [http://www.haidu.com. http://www.gg.com]
http://www.hd315.gov.cn/beian/view.asp?bianhao=010202006082400023 [http://www.tudou.com.
   http://www.vouku.coml
http://www.miibeian.gov.cn [http://www.gg.com. http://www.tudou.com. http://www.vouku.com]
http://www.miibeian.gov.cn/publish/query/indexFirst.action [http://www.tudou.com, http://www.youku.com]
http://www.pclady.com.cn [http://www.baidu.com, http://www.qq.com]
http://www.qq.com [http://www.baidu.com, http://www.qq.com]
http://www.shibzx.cn [http://www.gg.com. http://www.tudou.com]
http://www.tudou.com [http://www.tudou.com. http://www.youku.com]
http://www.tudou.com/about/cn [http://www.tudou.com, http://www.youku.com]
http://www.tudou.com/about/en [http://www.tudou.com, http://www.youku.com]
http://www.vouku.com [http://www.baidu.com, http://www.tudou.com, http://www.youku.com]
http://www.vouku.com/show.page/id_z8dc3fdeedcb911e3a705.html [http://www.tudou.com, http://www.youku.com]
http://v.gg.com [http://www.baidu.com, http://www.gg.com]
https://www.alipav.com [http://www.baidu.com. http://www.vouku.com]
```

#### **Summary**



- MapReduce via Hadoop can cover a use case of distributed computing that neither MPI nor Java Servlets can
- Easy to use with Java and Maven
- Apache Hadoop has many more features, which we cannot cover here



# 谢谢 Thank you

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#### Bibliography I



- Thilina Gunarathne. Hadoop MapReduce v2 Cookbook. Birmingham, UK: Packt Publishing Limited ebooks Account, 2nd revised edition, January 2015. ISBN 978-1783285471.
- Donald Miner and Adam Shook. MapReduce Design Patterns Building Effective Algorithms and Analytics for Hadoop and Other Systems. Sebastopol, CA, USA: O'Reilly Media, Inc., 2012. ISBN 978-1-4493-2717-0. URL http://filepi.com/i/VhKExiV.
- Tom White. Hadoop: The Definitive Guide Storage and Analysis at Internet Scale. Sebastopol, CA, USA: O'Reilly Media, Inc., 4th edition, March 2015. ISBN 978-1-4919-0163-2.
- 4. Jeffrey Dean and Sanjay Ghemawat. Mapreduce: Simplified data processing on large clusters. Technical report, Google, Inc., 2004. URL
  - http://static.googleusercontent.com/media/research.google.com/es/us/archive/mapreduce-osdi04.pdf. Appeared in OSDI'04: Sixth Symposium on Operating System Design and Implementation, San Francisco, CA, December, 2004 and Communications of the ACM 50th anniversary issue: 1958-2008 CACM Homepage archive. 51(1):107-113, January 2008, ACM New York, NY, USA.
- Jimmy Lin. Cloud Computing Lecture #1 What is Cloud Computing? (and an intro to parallel/distributed processing).
   College Park, MD, USA: University of Maryland, The iSchool, September 3, 2008. URL
   http://www.umiacs.umd.edu/~iimmylin/cloud~2008~Fall/Sessionl.ppt.
- Amr Awadallah. Stanford ee380 computer systems colloquium introducing apache hadoop: The modern data operating system, November 16, 2011. URL http://web.stanford.edu/class/ee380/Abstracts/111116-slides.pdf.