Distributed Text Mining with tm

Stefan Theußl[1] Ingo Feinerer[2] Kurt Hornik[1]

Department of Statistics and Mathematics,
WU Vienna University of Economics and Business[1]

Institute of Information Systems, DBAI Group
Technische Universität Wien[2]

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Text Mining in R

- Highly interdisciplinary research field utilizing techniques from computer science, linguistics, and statistics
- Vast amount of textual data available in machine readable format:
  - scientific articles, abstracts, books, ...
  - memos, letters, ...
  - online forums, mailing lists, blogs, ...
- Steady increase of text mining methods (both in academia as in industry) within the last decade

Text Mining in R

- `tm` Package
- Tailored for
  - Plain texts, articles and papers
  - Web documents (XML, SGML, ...)
  - Surveys
- Available *transformations*: `stemDoc()`, `stripWhitespace()`, `tmTolower()`, ...
- Methods for
  - Clustering
  - Classification
  - Visualization
- Feinerer (2009) and Feinerer et al. (2008)

Motivation

- Data volumes (corpora) become bigger and bigger
- Many tasks, i.e. we produce output data via processing lots of input data
- Text mining methods are becoming more complex and hence computer intensive
- Want to make use of many CPUs
- Typically this is not easy (parallelization, synchronization, I/O, debugging, etc.)
- Need for an integrated framework
- preferably usable on large scale distributed systems

$\rightarrow$ **Main motivation: large scale data processing**

Motivation

- Multi-processor environments and large scale compute clusters/clouds available for a reasonable price
- Integrated frameworks for parallel/distributed computing available (e.g., Hadoop)
- Thus, parallel/distributed computing is now easier than ever
- R already offers extensions to use this software (e.g. via hive, nws, Rmpi, snow, etc.)

Distributed Text Mining in R

Example: Stemming

- Erasing word suffixes to retrieve their radicals
- Reduces complexity
- Stemmers provided in packages Rstem[1] and Snowball[2]

Data:

- *Wizard of Oz* book series (`http://www.gutenberg.org`): 20 books, each containing 1529 – 9452 lines of text
- *Reuters-21578*: one of the most widely used test collection for text categorization research
- *New York Times Annotated Corpus*: $>$ 1.6 million text files

[1] Duncan Temple Lang (version 0.3-1 on Omegahat)
[2] Kurt Hornik (version 0.0-6 on CRAN)

Distributed Text Mining in R

Difficulties:

- Large data sets
- Corpus typically loaded into memory
- Operations on all elements of the corpus (so-called *transformations*)

Strategies:

- Text mining using tm and MapReduce/hive[1]
- Text mining using tm and MPI/snow[2]

[1] Stefan Theußl (version 0.1-1)
[2] Luke Tierney (version 0.3-3)

The MapReduce Programming Model

The MapReduce Programming Model

- Programming model inspired by functional language primitives
- Automatic parallelization and distribution
- Fault tolerance
- I/O scheduling
- Examples: document clustering, web access log analysis, search index construction, ...
- Dean and Ghemawat (2004)

Hadoop (`http://hadoop.apache.org/core/`) developed by the Apache project is an open source implementation of MapReduce.

The MapReduce Programming Model

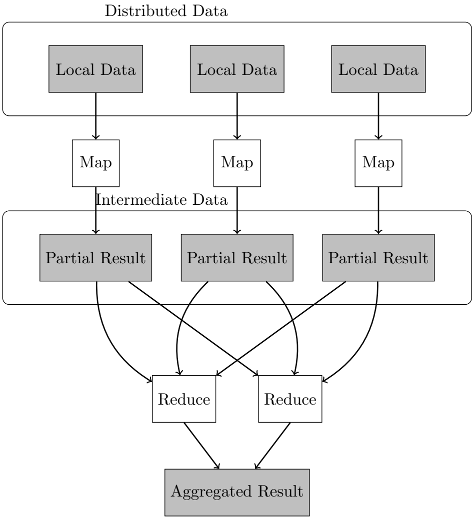


Figure: Conceptual Flow

The MapReduce Programming Model

A MapReduce implementation like Hadoop typically provides a distributed file system (DFS):

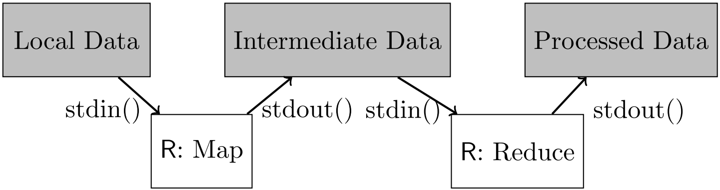
- Master/worker architecture (Namenode/Datanodes)
- Data locality
- Map tasks are applied to partitioned data
- Map tasks scheduled so that input blocks are on same machine
- Datanodes read input at local disk speed
- Data replication leads to fault tolerance
- Application does not care whether nodes are OK or not

Hadoop Streaming

- Utility allowing to create and run MapReduce jobs with any executable or script as the mapper and/or the reducer

```
$HADOOP_HOME/bin/hadoop jar $HADOOP_HOME/hadoop-streaming.jar
```

- `-input inputdir`
- `-output outputdir`
- `-mapper ./mapper`
- `-reducer ./reducer`



Hadoop InteractiVE (hive)

Hadoop InteractiVE (hive)

hive provides:

- Easy-to-use interface to Hadoop
- Currently, only Hadoop core (`http://hadoop.apache.org/core/`) supported
- High-level functions for handling Hadoop framework (`hive_start()`, `hive_create()`, `hive_is_available()`, etc.)
- DFS accessor functions in R (`DFS_put()`, `DFS_list()`, `DFS_cat()`, etc.)
- Streaming via Hadoop (`hive_stream()`)
- Available on R-Forge in project RHadoop

Example: Word Count

Data preparation:

```
> library("hive")
Loading required package: rJava
Loading required package: XML
> hive_start()
> hive_is_available()
[1] TRUE
> DFS_put("~/Data/Reuters/minimal", "/tmp/Reuters")
> DFS_list("/tmp/Reuters")
[1] "reut-00001.xml" "reut-00002.xml" "reut-00003.xml"
[4] "reut-00004.xml" "reut-00005.xml" "reut-00006.xml"
[7] "reut-00007.xml" "reut-00008.xml" "reut-00009.xml"
> head(DFS_read_lines("/tmp/Reuters/reut-00002.xml"))
[1] "<?xml version=\"1.0\"?>"
[2] "<REUTERS TOPICS=\"NO\" LEWISSPLIT=\"TRAIN\" [...]
[3] " <DATE>26-FEB-1987 15:03:27.51</DATE>"
[4] " <TOPICS/>"
[5] " <PLACES>"
[6] "  <D>usa</D>"
```

Example: Word Count

```r
mapper <- function(){
  mapred_write_output <- function(key, value)
    cat(sprintf("%s\t%s\n", key, value), sep = "")

  trim_white_space <- function(line)
    gsub("(^ +)|( +$)", "", line)
  split_into_words <- function(line)
    unlist(strsplit(line, "[[:space:]]+"))

  con <- file("stdin", open = "r")
  while (length(line <- readLines(con, n = 1,
                 warn = FALSE)) > 0) {
    line <- trim_white_space(line)
    words <- split_into_words(line)
    if(length(words))
      mapred_write_output(words, 1)
  }
  close(con)
}
```

Example: Word Count

```
reducer <- function(){
  [...]
  env <- new.env(hash = TRUE)
  con <- file("stdin", open = "r")
  while (length(line <- readLines(con, n = 1,
              warn = FALSE)) > 0) {
    split <- split_line(line)
    word <- split$word
    count <- split$count
    if(nchar(word) > 0){
      if(exists(word, envir = env, inherits = FALSE)) {
        oldcount <- get(word, envir = env)
        assign(word, oldcount + count, envir = env)
      }
      else assign(word, count, envir = env)
    }
  }
  close(con)
  for (w in ls(env, all = TRUE))
    cat(w, "\t", get(w, envir = env), "\n", sep = "")
}
```

Example: Word Count

```
> hive_stream(mapper = mapper,
              reducer = reducer,
              input = "/tmp/Reuters",
              output = "/tmp/Reuters_out")
> DFS_list("/tmp/Reuters_out")
[1] "_logs"        "part-00000"
> results <- DFS_read_lines(
               "/tmp/Reuters_out/part-00000")
> head(results)
[1] "-\t2"                 "--\t7"
[3] ":\t1"                 ".\t1"
[5] "0064</UNKNOWN>\t1" "0066</UNKNOWN>\t1"
> tmp <- strsplit(results, "\t")
> counts <- as.integer(unlist(lapply(tmp, function(x)
                                                 x[[2]])))
> names(counts) <- unlist(lapply(tmp, function(x)
                                             x[[1]]))
> head(sort(counts, decreasing = TRUE))
 the   to  and   of   at said
  58   44   41   30   25   22
```

Distributed Text Mining in R

Solution (Hadoop):

- Data set copied to DFS (‘`DistributedCorpus`’)
- Only meta information about the corpus in memory
- Computational operations (*Map*) on all elements in parallel
- Work horse `tmMap()`
- Processed documents (revisions) can be retrieved on demand

Distributed Text Mining in R - Listing

```
> library("tm")
Loading required package: slam
> input <- "~/Data/Reuters/reuters_xml"
> co <- Corpus(DirSource(input), [...])
> co
A corpus with 21578 text documents
> print(object.size(co), units = "Mb")
65.5 Mb

> source("corpus.R")
> source("reader.R")
> dc <- DistributedCorpus(DirSource(input), [...])
> dc
A corpus with 21578 text documents
> dc[[1]]
Showers continued throughout the week in
[...]
> print(object.size(dc), units = "Mb")
1.9 Mb
```

Distributed Text Mining in R - Listing

Mapper, i.e. input to `hive_stream()` (called by `tmMap()`):

```
mapper <- function(){
  require("tm")
  fun <- some_tm_method
  [...]
  con <- file("stdin", open = "r")
  while(length(line <- readLines(con, n = 1L,
                                 warn = FALSE)) > 0) {
    input <- split_line(line)
    result <- fun(input$value)
    if(length(result))
      mapred_write_output(input$key, result)
  }
close(con)
}
```

Distributed Text Mining in R

Infrastructure:

- Development platform: 8-core Power 6 shared memory system

IBM System p 550	
4	2-core IBM POWER6 @ 3.5 GHz
128	GB RAM

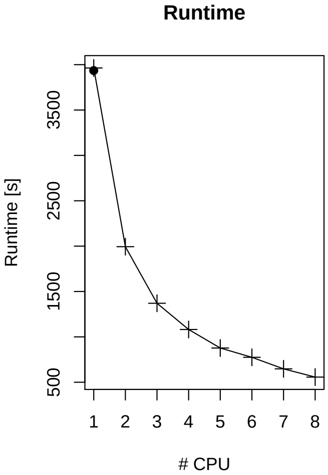
- Computers of PC Lab used as worker nodes
  - 8 PCs with an Intel Pentium 4 CPU @ 3.2 GHz and 1 GB of RAM
  - Each PC has > 20 GB reserved for DFS

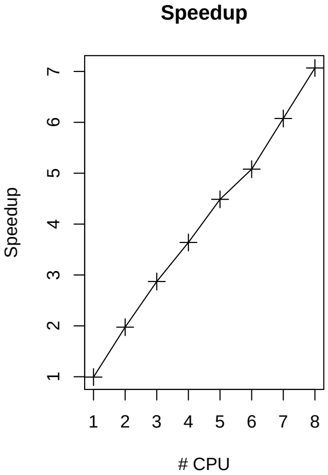
MapReduce framework:

- Hadoop (implements MapReduce + DFS)
- R (2.9.0) with tm (0.4) and hive (0.1-1)
- Code implementing `DistributedCorpus`
- Cluster installation coming soon (loose integration with SGE)

Benchmark

Wizard of Oz data set (PC Lab cluster):





Benchmark

Reuters-21578:

- Single processor runtime (`lapply()`): $>$ 30 min.
- tm/hive on 8-core SMP (`hive_stream()`): 4 min.
- tm/snow on 8 nodes of cluster@WU (`parLapply()`): 2.13 min.

Lessons Learned

- Problem size has to be sufficiently large
- Requirement: access text documents in R via [[, thus location of texts in DFS important (currently: ID = file path)
- Serialization difficult: how updating text IDs? Currently via meta information to each chunk (chunk name, position in the chunk)
- Remote file operation on DFS around 2.5 sec. (significantly reduced with Java implementation)

Conclusion

- Use of Hadoop in particular the DFS enhances handling of large corpora
- Significant speedup in text mining applications
- Thus, MapReduce has proven to be a useful abstraction
- Greatly simplifies distributed computing
- Developer focus on problem
- Implementations like Hadoop deal with messy details
  - different approaches to facilitate Hadoop's infrastructure
  - language- and use case dependent

Thank You for Your Attention!

Stefan Theußl
Department of Statistics and Mathematics
email: `Stefan.Theussl@wu.ac.at`
URL: `http://statmath.wu.ac.at/~theussl`

WU Vienna University of Economics and Business
Augasse 2–6, A-1090 Wien

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