Efficient Analysis of Big Data and Big Models through Distributed Computation

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Why Move to Distributed Computation?

"In pioneer days they used oxen for heavy pulling, and when one ox couldn't budge a log, they didn't try to grow a larger ox. We shouldn't be trying for bigger computers, but for more systems of computers."

-Grace Hopper

Hadoop

- An open source framework for distributed computing
- Two primary subprojects:
  - MapReduce: distributed data processing
  - HDFS: distributed data storage
- MapReduce jobs typically written in Java
- Hadoop Streaming: API for using MapReduce with other languages
  - E.g., Ruby, Python, R
- Additional subprojects: Pig, HBase, ZooKeeper, Hive, Chuckwa, etc.

MapReduce in Detail

- A two step paradigm for big data processing
- To implement:
  - Specify key-value pairs as input & output for each phase
  - Specify two functions: map function and reduce function
- Map phase: perform a transformation (e.g., field-extraction, parsing, filtering) on each individual piece of data (e.g., row of text, tweet, vector) and output a key-value pair
- Reduce phase: (1) sort and group output by key, (2) compute an aggregate function over the values associated with each key, (3) output aggregates to disk

Hadoop vs. Other Parallelization Approaches

- Other Parallelization Approaches:
  - Break tasks up by hand, submit pieces individually to HPCs
  - Split tasks via other parallelization paradigms (e.g., MPI)
- Hadoop Drawbacks:
  - More complex (debugging, configuration)
  - Less intuitive, steep learning curve
  - Availability & access
  - Bleeding edge
- Hadoop Benefits:
  - Flat scalability & efficient processing
  - Open Source
  - Integration with other languages, computing tasks
  - Reliable/robust big data storage and processing

Hadoop on SDSC's 'Gordon' Supercomputer

- Overviews of Gordon can be found here and here
- Available via the NSF's Extreme Science and Engineering Discovery Environment (XSEDE)
  - Register at XSEDE (free)
  - Request or join (via, e.g., PSU's Campus Champion Allocation) a Gordon-Allocation (not always free)
- Benefits:
  - Full base Hadoop framework available (see here)
  - Easy Hadoop job scheduling/submission via MyHadoop
- Drawbacks (as of April 2013):
  - Hadoop compliments (e.g., Hive, HBase, Pig) aren't available
  - Relevant libraries for (e.g.,) R and Python aren't installed

A Selection of Hadoop's Built-in (Java) Example Scripts

- **wordcount**: A map/reduce program that counts the words in the input files
- **aggregatewordcount**: Aggregate map/reduce program to count words in input files
- **multifilewc**: A job that counts words from several files
- **grep**: A map/reduce program that counts the matches of a regex in the input
- **dbcount**: An example job that counts the pageview counts from a database
- **randomwriter**: A map/reduce program that writes 10GB of random data per node
- **randomtextwriter**: A map/reduce program that writes 10GB random text per node
- **sort**: A map/reduce program that sorts the data written by the random writer
- **secondarysort**: An example defining a secondary sort to the reduce
- **teragen/terrasort/teravalidate**: terabyte generate/sort/transfer
- **pi**: A map/reduce program that estimates Pi using a monte-carlo method

For online tutorials on these, see here, here, and here.

Running Example: ICEWS News-Story Corpus

- 60 European and Middle Eastern countries
- All politically relevant stories, January 2001 to July 2011
- Document: Individual news-story (first 3-4 sentences)
- 6,681,537 Stories
- Removed: punctuation, stopwords, numbers, proper nouns, etc.
- Stemmed words

Applying wordcount to Entire News-Story Corpus

- What are the most frequent (stemmed) words?
- Map Stage: assign <key,value> pairs to corpus
  - Read in X-lines (stories) of text from corpus
  - Input <key,value>: <line-number, line-of-text>
  - Output <key,value>: <word, one>
- Reduce Stage: sum individual <key, value>'s from Map tasks
  - Input <key,value>: <word, one>
  - Output <key,value>: <word, occurrence>
- 1 Node→ 8 minutes; 4 Nodes→ 5 minutes
- 406,466 unique "words"

For online tutorials on Hadoop's wordcount, see here, here, and here.

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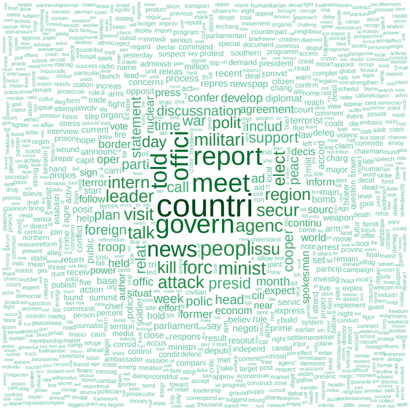
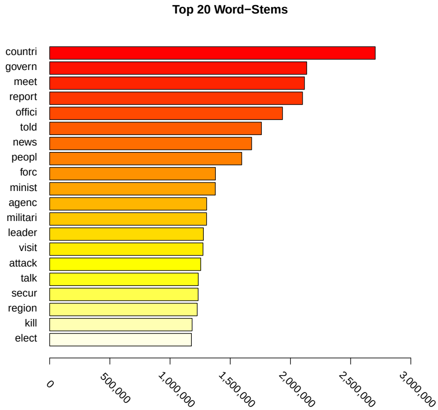
Word-Stem Frequencies for ICEWS News Corpus





Cluster Analysis of Country News-Reports

- Do country-news reports cluster in interesting ways?
- K-Means on all 60 countries' news reports (1000 per country)
- Specify 60 clusters and set no. of iterations to 10
- Examine variation in cluster assignments across countries

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K-Means with MapReduce/Java

- Map Stage: assign word values to (new) minimum distance clusters
    - Read in vectorized story-words (vv), and previous centers
    - For each word (v), apply distance function to find nearest center
    - Output <key,value>: <center$_i$,v>
- Reduce Stage: row bind and average <key, value>'s from Map tasks
    - Input <key,value>: <center$_i$, v >
    - Output: New center$_i$ $= mean(< center_i, vv >)$
- Non-Hadoop→1hr, 45 min; Hadoop→51 minutes

For running K-Means in Java, see here. For extending K-Means in Java to MapReduce and Hadoop, see here.

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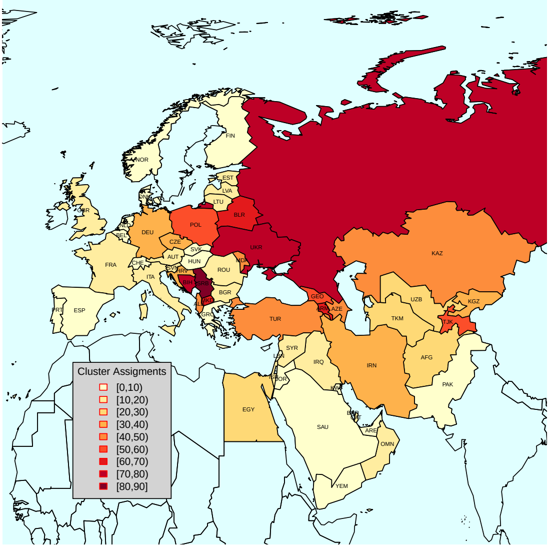
Cluster 4


Cluster Assigments
[0,10)
[10,20)
[20,30)
[30,40)
[40,50)
[50,60)
[60,70)
[70,80)
[80,90]
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NOR
EST
LVA
LTU
BLR
POL
DEU
GBR
NLD
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SVK
UKR
KAZ
AUT
HUN
FRA
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GEO
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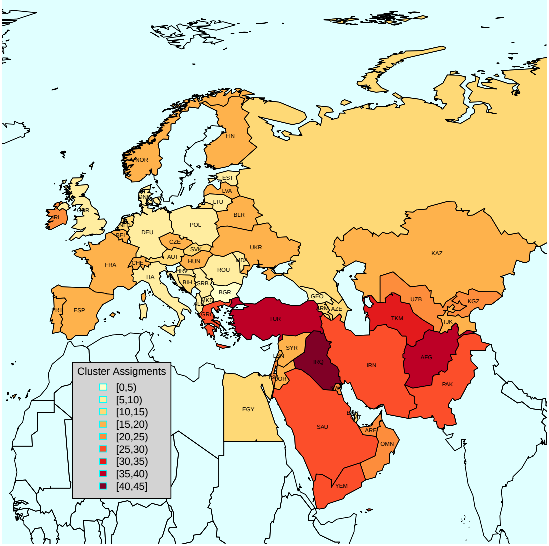
YEM

Cluster 7


Cluster Assigments
[0,5)
[5,10)
[10,15)
[15,20)
[20,25)
[25,30)
[30,35)
[35,40)
[40,45]
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NOR
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BLR
GBR
IRL
NLD
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POL
CZE
SVK
UKR
AUT
HUN
MDA
FRA
CHE
ITA
HRV
BIH
SRB
ROU
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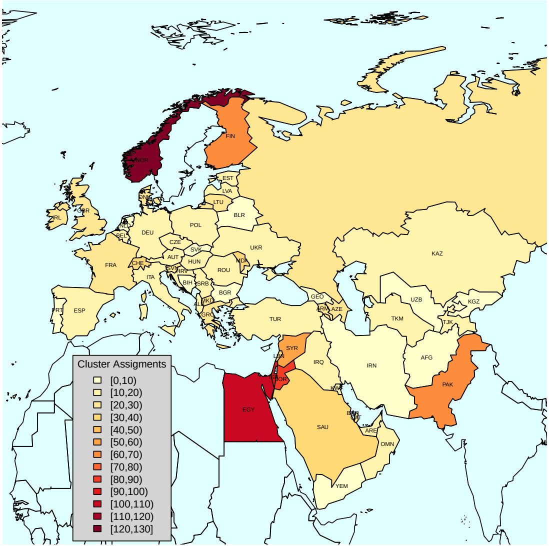
EGY

Cluster 40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[110,120)
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Moving from Hadoop/Java to RHadoop

- Write and implement Hadoop jobs in R via Hadoop Streaming
- This requires three RHadoop packages: rhdfs, rmr, rhbase
    - Also requires additional prerequisite packages (e.g., rJava)
    - Also requires that you install and build Thrift
- Install & set-up Hadoop, RHadoop, and Streaming on EC2
- Use Amazon Elastic MapReduce (EMR) to run RHadoop via Streaming

Overviews of RHadoop, and installation info: here, here, here, and here.

Ready-Made Examples for RHadoop

- Basic data analysis
- Word count
- Logistic Regression
- K-Means (also here)
- Linear Least Squares

Getting Started on Hadoop

- For those interested in trying out Hadoop on Gordon...
- QuaSSIHadoop.zip
- Readme, .sh scripts, output files, error files, and all necessary input files for 4 basic Hadoop jobs:
  - Simple: a simple setup and usage example
  - TestDFS: depth-first search (DFS) benchmark
  - TeraSort: sorting benchmark
  - Wordcount: word frequencies

Questions?

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