CS 535 Large Scale Data Analysis

Amit Jain

Big Data, Big Disks, Cheap Computers

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- *"More data usually beats better algorithms."* Anand Rajaraman.
- *"The good news is that Big Data is here. The bad news is that we are struggling to store and analyze it."* Tom White.

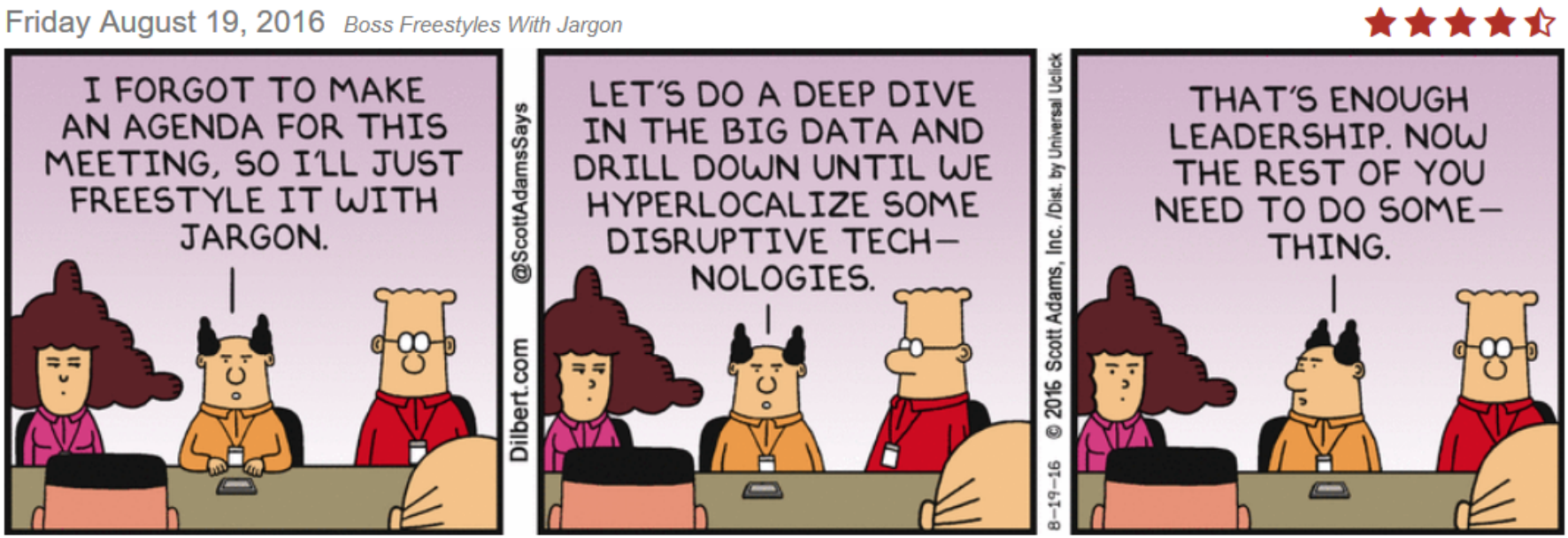
Units and Units

Check out http://en.wikipedia.org/wiki /Petabyte

Big Data


Big Data knows everything
CONSULTANTS SAY THREE QUINTILLION BYTES OF DATA ARE CREATED EVERY DAY.
DilbertCartoonist@gmail.com
IT COMES FROM EVERYWHERE. IT KNOWS ALL.
ACCORDING TO THE BOOK OF WIKIPEDIA, ITS NAME IS "BIG DATA."
BIG DATA
©2012 Scott Adams, Inc.
BIG DATA LIVES IN THE CLOUD. IT KNOWS WHAT WE DO.
IN THE PAST, OUR COMPANY DID MANY EVIL THINGS.
BUT IF WE ACCEPT BIG DATA IN OUR SERVERS, WE WILL BE SAVED FROM BANKRUPTCY.
LET US PAY.
$
www.dilbert.com
7-29-12
IS IT TOO LATE TO SIDE WITH EVIL?
SHHHH! IT HEARS YOU.

Big Data


Friday August 19, 2016 Boss Freestyles With Jargon
I FORGOT TO MAKE AN AGENDA FOR THIS MEETING, SO I'LL JUST FREESTYLE IT WITH JARGON.
LET'S DO A DEEP DIVE IN THE BIG DATA AND DRILL DOWN UNTIL WE HYPERLOCALIZE SOME DISRUPTIVE TECH-NOLOGIES.
THAT'S ENOUGH LEADERSHIP. NOW THE REST OF YOU NEED TO DO SOME-THING.
Dilbert.com @ScottAdamsSays
8-19-16 © 2016 Scott Adams, Inc. /Dist. by Universal Uclick

Big Data


DO WE HAVE ANY ACTIONABLE ANALYTICS FROM OUR BIG DATA IN THE CLOUD?
YES, THE DATA SHOWS THAT MY PRODUCTIVITY PLUNGES WHENEVER YOU LEARN NEW JARGON.
MAYBE IN-MEMORY COMPUTING WILL ACCEL-ERATE YOUR APPLICA-TIONS.
PLUNGE, PLUNGE, PLUNGE.
Dilbert.com DilbertCartoonist@gmail.com
1-9-13 ©2013 Scott Adams, Inc./Dist. by Universal Uclick

Word-count: Hello World of Big Data

Problem: Given a collection of text files, find the frequency of each word.

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File1.txt	File2.txt	File3.txt
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Result:

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big 3
data 4
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Questions: Do we want the output sorted by frequency? Sorted by word? How would you solve this problem?

Sequential Solutions (1)

```
create empty dictionary
for f over all input files
    open file f
    while not end of file f
        read next word
        if search(word, dictionary)
            increment frequency count for word
        else
            add word to the dictionary

open output file
iterate over dictionary
    write next word to output file
```

Sequential Solutions 1 (Analysis)

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- So the main loop takes $O(n)$ time on average and $O(n \lg n)$ in the worst case
- The time to output is insignificant as the size of the dictionary will be much smaller than n. Why?

Examples

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  - The first command `cat` outputs all the files into one stream to the next program `tr` in the pipeline.
  - The `tr` command breaks the words in each line into a line by itself and then streams them to the `sort` command.
  - After sorting, all instances of a word are together, which `uniq -c` counts and outputs.

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- How do you modify your solution from before? Assume that you have a cluster of n servers available with the files distributed across the servers.
- But how do we create a cluster and get the files on it?

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- What if some of the server disks fail or get corrupted while your program is running?
- What if the some system administrator reboots some of your servers for software/hardware updates without letting you know?

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- Typical languages would be Java (with Hadoop and/or Spark), Scala, Python (at smaller scales)

Insights from Big Data

The point of large scale data analysis is meaningful insight!
We should consider two things about insights presented by analysis:

- Investigate carefully to see if it uses a significant amount of data.
- Think about each of the insights and label them Actionable, Useless (trivia), or potentially Misleading or dangerous.

For example:
https://blogs.scientificamerican.com/guest-blog/9-bizarre-and-surprising-insights-from-data-science/