CS 535 Large Scale Data Analysis

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Big Data, Big Disks, Cheap Computers

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- ► "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



Big Data

Friday August 19, 2016 Boss Freestyles With Jargon





Big Data





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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)

```
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 dicitionary
 write next word to output file

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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?

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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 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 (1)

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 really 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:

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