Big Data is Not About the Data!

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\[1\]GaryKing.org
The Data In Big Data (about people)
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The Last 50 Years:

• Survey research
• Aggregate government statistics
• One off studies of individual places, people, or events

The Next 50 Years: Fast increases in new data sources, due to:

• Much more of the above — improved, expanded, and applied
• Shrinking computers & the growing Internet: data everywhere
• The march of quantification: through academia, professions, government, & commerce
• The replication movement: data sharing (e.g., Dataverse)
• Governments encouraging data collection & experimentation
• Advances in statistical methods, informatics, & software

Impact:

— changed most Fortune 500 firms
— established new industries
— altered friendship networks, political campaigns, public health, legal analysis, policing, economics, sports, public policy, literature, etc., etc., etc.
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The *Value* in Big Data: the Analytics

- **Easy to come by; often a free byproduct of IT improvements**
- **Becoming commoditized**
- **Ignore it & every institution will have more every year**
- **With a bit of effort: huge data production increases**

**Where the Value is: the Analytics**

- **Output can be highly customized**
- **Moore's Law (doubling speed/power every 18 months)**
- **$2M computer v. 2 hours of algorithm design**
- **Low cost; little infrastructure; mostly human capital needed**
- **Innovative analytics: enormously better than off-the-shelf**
The *Value* in Big Data: the Analytics

- Data:
  - Data is often easy to come by, often a free byproduct of IT improvements.
  - It is becoming commoditized.
  - Ignore it, and every institution will have more every year.
  - With a bit of effort, huge data production increases can be achieved.

Where the Value is: the Analytics

- Output can be highly customized.
- Moore's Law (doubling speed/power every 18 months) vs. One good data scientist (1000x speed increase in 1 day).
- $2$M computer vs. 2 hours of algorithm design.
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How to Read a Trillion Social Media Posts & Classify Deaths without Physicians

Examples of Bad Analytics:
- Physicians' "Verbal Autopsy" analysis
- Sentiment analysis via word counts

Unrelated substantive problems, same analytics solution:
- Key to both methods: classifying (deaths, social media posts)
- Key to both goals: estimating %'s

Modern Data Analytics: New method led to:
How to Read a Trillion Social Media Posts & Classify Deaths without Physicians

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- Modern Data Analytics: New method led to:
  1. Worldwide cause-of-death estimates for
Thresher: Finding Those Hiding in Plain Sight

Example Substitution 1:
Thresher: Finding Those Hiding in Plain Sight

Example Substitution 1:

自由
Thresher: Finding Those Hiding in Plain Sight

Example Substitution 1:

自由 “Freedom”
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自由："Freedom"
Thresher: Finding Those Hiding in Plain Sight

Example Substitution 1:

自由
自由
“Freedom”
目田
目田
“Eye field”
Example Substitution 1:

自由 “Freedom”
目田 “Eye field” (nonsensical)
Example Substitution 1: Homograph

自由
自由
“Freedom”
“Eye field” (nonsensical)
Thresher: Finding Those Hiding in Plain Sight

Example Substitution 1: Homograph

自 由  “Freedom”
目  田  “Eye field” (nonsensical)
Thresher: Finding Those Hiding in Plain Sight

Example Substitution 1: Homograph

自由 “Freedom”
目地 “Eye field” (nonsensical)

Example Substitution 2:
Thresher: Finding Those Hiding in Plain Sight

Example Substitution 1: Homograph

自由 “Freedom”
自由 “Eye field” (nonsensical)

Example Substitution 2:

和 谐
Thresher: Finding Those Hiding in Plain Sight

Example Substitution 1: Homograph

自由 “Freedom”
目田 “Eye field” (nonsensical)

Example Substitution 2:

和谐 “Harmonious [Society]” (official slogan)
Thresher: Finding Those Hiding in Plain Sight

Example Substitution 1: Homograph

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目田 “Eye field” (nonsensical)

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Example Substitution 1: Homograph

自由　“Freedom”
目田　“Eye field” (nonsensical)

Example Substitution 2:

和谐　“Harmonious [Society]” (official slogan)
河蟹
Example Substitution 1: Homograph

自由 “Freedom”
目田 “Eye field” (nonsensical)

Example Substitution 2:

和谐 “Harmonious [Society]” (official slogan)
河蟹 “River crab”
Thresher: Finding Those Hiding in Plain Sight

Example Substitution 1: Homograph

自由 “Freedom”
目 “Eye field” (nonsensical)

Example Substitution 2:

和 谐 “Harmonious [Society]” (official slogan)
河 蟹 “River crab” (irrelevant)
Example Substitution 1: Homograph

自 由  “Freedom”
目  田  “Eye field” (nonsensical)

Example Substitution 2: Homophone (sound like “hexie”)

和  谐  “Harmonious [Society]” (official slogan)
河  蟹  “River crab” (irrelevant)
Thresher: Finding Those Hiding in Plain Sight

Example Substitution 1: Homograph

自由 自由
自由 “Freedom”
目田 “Eye field” (nonsensical)

Example Substitution 2: Homophone (sound like “hexie”)

和 谐 和 谐
和 谐 “Harmonious [Society]” (official slogan)
河 蟹 河 蟹
河 蟹 “River crab” (irrelevant)

They can’t follow the conversation;
Thresher: Finding Those Hiding in Plain Sight

Example Substitution 1: Homograph

自由
自“Freedom”
自由
由“Eye field” (nonsensical)

Example Substitution 2: Homophone (sound like “hexie”)

和谐
和“Harmonious [Society]” (official slogan)
河蟹
河“River crab” (irrelevant)

They can’t follow the conversation; Thresher can.
Example Substitution 1: Homograph

自由  “Freedom”
目田 “Eye field” (nonsensical)

Example Substitution 2: Homophone (sound like “hexie”)

和谐 “Harmonious [Society]” (official slogan)
河蟹 “River crab” (irrelevant)

They can’t follow the conversation; Thresher can.
The same task:
Thresher: Finding Those Hiding in Plain Sight

Example Substitution 1: Homograph

自由 “Freedom”
目田 “Eye field” (nonsensical)

Example Substitution 2: Homophone (sound like “hexie”)

和谐 “Harmonious [Society]” (official slogan)
河蟹 “River crab” (irrelevant)

They can’t follow the conversation; Thresher can.
The same task: (1) Long tail search,
Thresher: Finding Those Hiding in Plain Sight

Example Substitution 1: Homograph

自由 自由 “Freedom” (censored)
目 田 目田 “Eye field” (nonsensical)

Example Substitution 2: Homophone (sound like “hexie”)

和 谐 和谐 “Harmonious [Society]” (official slogan) (censored)
河 蟹 河蟹 “River crab” (irrelevant)

They can’t follow the conversation; Thresher can.
The same task: (1) Long tail search, (2) Government and industry analyst’s job,
Thresher: Finding Those Hiding in Plain Sight

Example Substitution 1: Homograph

自由 “Freedom” (censored)
目田 “Eye field” (nonsensical)

Example Substitution 2: Homophone (sound like “hexie”)

和 谐 “Harmonious [Society]” (official slogan) (censored)
河 蟹 “River crab” (irrelevant)

They can’t follow the conversation; Thresher can.
The same task: (1) Long tail search, (2) Government and industry analyst’s job, (3) language drift (#BostonBombings ⇝ #BostonStrong),
Thresher: Finding Those Hiding in Plain Sight

Example Substitution 1: Homograph

自由
“Freedom” (censored)
目田
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和谐
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河蟹
“River crab” (irrelevant)

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自由
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They can’t follow the conversation; Thresher can.

The same task: (1) Long tail search, (2) Government and industry analyst’s job, (3) language drift (#BostonBombings ⇝ #BostonStrong), (4) Child pornographers, (5) Look-alike modeling, (6) Starting point for other automated text methods,
**Thresher: Finding Those Hiding in Plain Sight**

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自由
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和 谐
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“Harmonious [Society]” (official slogan)
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They can’t follow the conversation; Thresher can.

The same task: (1) Long tail search, (2) Government and industry analyst’s job, (3) language drift (#BostonBombings ⇝ #BostonStrong), (4) Child pornographers, (5) Look-alike modeling, (6) Starting point for other automated text methods, (7) Infinitely improvable classification, eDiscovery, etc., etc.
To understand many documents, humans create categories to represent conceptualization, insight, etc.

Most organizations: impose fixed categorizations to tally complaints, sort reports, retrieve information.

Bad Analytics:

- Unassisted Human Categorization: time consuming; huge efforts trying not to innovate!
- Fully Automated "Cluster Analysis": Many widely available, but none work (computers don't know what you want!)

Our alternative: Computer-assisted Categorization

- You decide what's important, but with help
- Invert effort: you innovate; the computer categorizes
- Insights: easier, faster, better

Technology: visualize the space of all possible clusterings

(Lots of technology, but it's behind the scenes)
Computer-Assisted Reading (Consilience)

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Example Insight from Computer-Assisted Reading

- Data: 64,000 Senators' press releases
- Categorization: (1) advertising, (2) position taking, (3) credit claiming
- New Insight: partisan taunting
  - Joe Wilson during Obama's State of the Union: "You lie!"
  - "Senator Lautenberg Blasts Republicans as 'Chicken Hawks'"
  - Basically anything said by a 2016 presidential candidate!
- How common is it? 27% of all Senatorial press releases!
Example Insight from Computer-Assisted Reading

What Members of Congress Do

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Modern Analytics to Improve Student Learning

The problem:

- How many students do reading assignments?
  - 20-30%
- How many students buy the book?
  - < 50%
- How much time do instructors have to write detailed quizzes?

Our solution:

Perusall

- A new type of (award-winning, patent pending) collaborative e-reader, using novel data analytics, and cutting-edge behavioral research
- > 90% of students do the reading
- Solitary reading assignments ⇝ engaging collective activities
- Intrinsic motivation: collaborative annotation in threads
- Extrinsic motivation: automated grading of annotations & engagement (better than instructors can do on their own)
- Novel data analytics: keep students on track, with automated personal guidance, nudges, nonadversarial grading
- Instructors save time, stay engaged: automated student confusion reports

Want to try it here? see Perusall.com
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  • Want to try it here? see Perusall.com
Modern Analytics to Improve Student Learning

- **The problem:**
  - How many students do reading assignments?

- **Perusall**
  - A new type of (award-winning, patent pending) collaborative e-reader, using novel data analytics, and cutting-edge behavioral research
  - > 90% of students do the reading
  - Solitary reading assignments ⇝ engaging collective activities
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• Previous approach: watch a few posts; see what’s removed
• Data: Download all posts before the Chinese censor them
• ≈ 13% censored overall

What Could be the Goal?

1. Stop collective action
   • Implications: Social Media is Actionable!
   • Chinese leaders:
     • measure criticism: to judge local officials
     • censor: to stop events with collective action potential
   • Thus, we can use criticism & censorship to predict:
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Evidence? A few anecdotes; “no ground truth”; “no successful attempts to quantify” 50c party activity; even several analyses with made up dependent variables!
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- Prevailing view of scholars, activists, journalists, social media participants: **50c party argues against those who criticize the government, its leaders, and their policies** *Wrong*
- Does not argue; does not engage on controversial issues
- Distracts; redirects public attention from criticism and central issues to **cheerleading** and positive discussions of valence issues
The End of The Quantitative-Qualitative Divide

• The Quant-Qual divide exists in every field.
• Qualitative researchers: overwhelmed by information; need help.
• Quantitative researchers: recognize the huge amounts of information in qualitative analyses, starting to analyze unstructured text, video, audio as data.
• Expert-vs-analytics contests: Whenever enough information is quantified, a right answer exists, and good analytics are applied: analytics wins.
• Moral of the story:
  • Fully human is inadequate
  • Fully automated fails
  • We need computer assisted, human controlled technology
    (Technically correct, & politically much easier)
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How To Take Advantage of Big Analytics

- It's cheap and powerful; don't skimp!
- Off-the-shelf analytics ⇝ big advances
- Innovative analytics ⇝ immensely better than off-the-shelf
- Save it for last first!

- The goal is "inference": using facts you know to learn about facts you don't know
- The uncertainties in inference: not having the facts you need (most statistics are designed solely to overcome data problems)
- Building analytics during design:
  - avoids problems before they occur
  - saves a fortune,
  - opens many more possibilities
- Build a new discipline of data science
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• Its cheap and powerful; don’t skimp!
  • Off-the-shelf analytics $\rightsquigarrow$ big advances
  • Innovative analytics $\rightsquigarrow$ immensely better than off-the-shelf

• Save it for last first!
  • The goal is “inference”:
    using facts you know to learn about facts you don’t know
  • The uncertainties in inference: not having the facts you need
    (most statistics are designed solely to overcome data problems)
  • Building analytics during design:
    • avoids problems before they occur
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• Build a new discipline of data science
For more information

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