Big Data is Not About the Data!

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Michigan State University 10/6/2016

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The Data in Big Data (about people)

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

- Data: 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) vs. One good data scientist (1000x speed increase in 1 day).
- $2M computer vs. 2 hours of algorithm design.
- Low cost; little infrastructure; mostly human capital needed.
- Innovative analytics: enormously better than off-the-shelf.
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- Opinions of activists:
  - A few thousand interviews
  - Billions of political opinions in social media posts (650M/day)

- Exercise:
  - A survey: "How many times did you exercise last week?"
  - 500K people carrying cell phones with accelerometers

- Social contacts:
  - A survey: "Please tell me your 5 best friends"
  - Continuous record of phone calls, emails, text messages, bluetooth, social media connections, address books

- Economic development in developing countries:
  - Dubious or nonexistent governmental statistics
  - Satellite images of human-generated light at night, road networks, other infrastructure

- Many, many, more...

In each: without new analytics, the data are useless
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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:

1. Worldwide cause-of-death estimates for 5/15
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[Image of Crimson Hexagon advertisement]
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Bias in U.S. Social Security Administration Forecasts

Social Security: single largest government program; lifted a whole generation out of poverty; extremely popular

Forecasts: used for programs comprising > 50% of the US expenditures; e.g., if retirees draw benefits longer than expected, the Trust Fund runs out

First evaluation of SSA forecasts in 85 years:

Methods: little changed; mostly qualitative; a time when we've learned more about forecasting than at any time in history

Results: unbiased until 2000; systematically biased after

Actuaries hunkered down, insulated themselves, refused to budge when Democrats & Republicans pushed hard for changes

In the process, they also insulated themselves from the facts: Especially since 2000, Americans started living unexpectedly longer lives (due to statins, early cancer detection, etc.)

New customized analytics we developed:

Logical consistency (e.g., older people have higher mortality)

Far more accurate forecasts

⇝ Trust fund needs > $800 billion more than SSA thought

Many other applications to different types of forecasts
Bias in U.S. Social Security Administration Forecasts

- Social Security: single largest government program; lifted a whole generation out of poverty; extremely popular

- Forecasts: used for programs comprising >50% of the US expenditures; e.g., if retirees draw benefits longer than expected, the Trust Fund runs out

- First evaluation of SSA forecasts in 85 years:
  - Methods: little changed; mostly qualitative; a time when we've learned more about forecasting than at any time in history
  - Results: unbiased until 2000; systematically biased after
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Thresher: Finding Those Hiding in Plain Sight
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Example Substitution 1:
Example Substitution 1:

自由
Example Substitution 1:

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

Example Substitution 1:

自由  “Freedom”  [Censored]
Example Substitution 1:

自 由
“Freedom”

目 田

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

Example Substitution 1:

自由
“Freedom”

目田
“Eye field”
Thresher: Finding Those Hiding in Plain Sight

Example Substitution 1:

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

Example Substitution 1: Homograph

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

自由  “Freedom”
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Example Substitution 2:
Thresher: Finding Those Hiding in Plain Sight

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

Example Substitution 2:

和谐
Thresher: Finding Those Hiding in Plain Sight

Example Substitution 1: Homograph

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

Example Substitution 2:

和 谐 “Harmonious [Society]” (official slogan)
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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)
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Example Substitution 2: Homophone (sound like “hexie”)

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河蟹  “River crab” (irrelevant)

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

**Example Substitution 1: Homograph**

<table>
<thead>
<tr>
<th>自由</th>
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</tr>
</thead>
<tbody>
<tr>
<td>目田</td>
<td>“Eye field” (nonsensical)</td>
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</table>

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

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Thresher: Finding Those Hiding in Plain Sight

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The same task:
Thresher: Finding Those Hiding in Plain Sight

Example Substitution 1: Homograph

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They can’t follow the conversation; Thresher can.
The same task: (1) Long tail search,
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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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Data: 64,000 Senators' press releases

Categorization: (1) advertising, (2) position taking, (3) credit claim

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!
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What Members of Congress Do

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  - “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!
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Modern Analytics to Improve Student Learning

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  • How many students buy the book?: <50%
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• Our solution:
  • Perusall
    • A new type of collaborative e-reader
    • With 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
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Reverse Engineering Censorship in China

Previous approach: watch a few posts; see what's removed

Data: Download all posts before the Chinese censor them

Novel methods of automated text analysis to discover patterns

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:

• Officials in trouble, likely to be replaced
• Dissident arrests; new peace treaties; emerging scandals
• Disagreements between central and local leaders
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The Government Surreptitiously Fabricating Social Media Posts
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- Prevailing view of scholars, activists, journalists, social media participants:
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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
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Our evidence:
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Our evidence: (1) Found a leaked archive of 50c posts too hard to analyze, (2) developed methods of automated text analysis to decipher, (3) discovered patterns and extrapolated to all of China, (4) did a poll(!) and predicted 50c members acknowledged their behavior
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The Government Surreptitiously Fabricating Social Media Posts

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- 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)
The End of The Quantitative-Qualitative Divide

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• 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

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For more information

GaryKing.org

Institute for Quantitative Social Science
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