Big Data is Not About the Data!
The Power of Modern Analytics

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Civil Service College, Singapore 8/19/2016
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 replication movement: data sharing (e.g., Dataverse)
• Governments encouraging data collection & experimentation
• Advances in statistical methods, informatics, & software
• The march of quantification: through academia, professions, government, & commerce (SuperCrunchers, The Numerati, MoneyBall, and innumerable "big data" articles)

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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- literature, etc., etc., etc.

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- 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 v. 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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Exciting Data, But Useless without Novel Analytics

- Opinions of activists: A few thousand interviews \(\Rightarrow\) billions of political opinions in social media posts (650M/day)
- Exercise: A survey: "How many times did you exercise last week?" \(\Rightarrow\) 500K people carrying cell phones with accelerometers
- Social contacts: A survey: "Please tell me your 5 best friends" \(\Rightarrow\) continuous record of phone calls, emails, text messages, bluetooth, social media connections, address books
- Economic development in developing countries: Dubious or nonexistent governmental statistics \(\Rightarrow\) 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
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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
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⇒ Trust fund needs >$800 billion more than SSA thought

Many other applications to different types of forecasts
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Humans are Horrible at Thinking of Keywords

An experiment:
“We have 10,000 twitter posts, each containing the word 'healthcare', from the time period surrounding the Supreme Court decision on Obamacare. Please list any keywords which come to mind that will select posts in this set related to Obamacare and will not select posts unrelated to Obamacare.”

Examples:
unconstitutional, coverage, obama, ACA...

Median keywords recalled: 8
Unique keywords recalled by 43 undergrads: 149
Keywords 42 of 43 failed to recall: 98 (66%)

⇝ Humans recognize keywords well, recall them poorly

Thresher: New technology to discover the right keywords
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Thresher: Finding Those Hiding in Plain Sight
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Example Substitution 1:
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自由

"Freedom" (nonsensical)

目
田

"Eye field" (nonsensical)
Thresher: Finding Those Hiding in Plain Sight

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自由 “Freedom”
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“Freedom”

目田

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.
Thresher: Finding Those Hiding in Plain Sight

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“Freedom”
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Example Substitution 1:

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

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Example Substitution 1: Homograph

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

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

Example Substitution 1: Homograph

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

Example Substitution 2:

和谐
Thresher: Finding Those Hiding in Plain Sight

Example Substitution 1: Homograph

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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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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:

和 谐 和 谐
“Harmonious [Society]” (official slogan)
河蟹 “River crab”
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The same task: (1) Long tail search, (2) Government and industry analyst’s job,
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目  “Eye field”  (nonsensical)

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

和 谐  “Harmonious [Society]”  (official slogan)  [CENSORED]
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The same task: (1) Long tail search, (2) Government and industry analyst’s job, (3) language drift (\#BostonBombings $\Rightarrow$ \#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)
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Example Insight from Computer-Assisted Reading

What Members of Congress Do

• 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!
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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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• 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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- Prevailing view of scholars, activists, journalists, social media participants:
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Evidence? A few anecdotes; “no ground truth”; “no successful attempts to quantify” 50c party activity;
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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*

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

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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

• Build a new discipline of data science
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