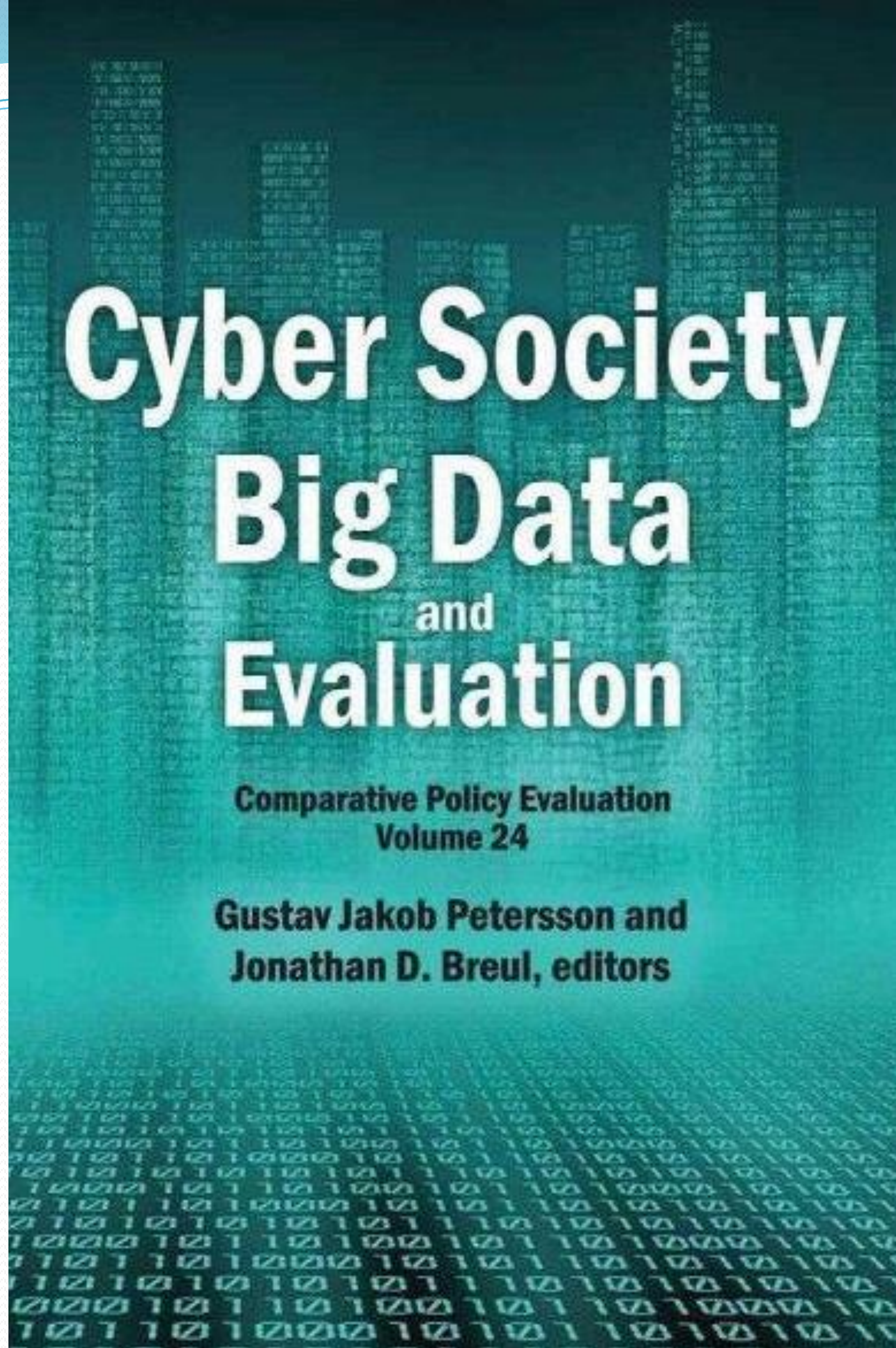
A potentially happy marriage: Evaluation + Big Data

Norwegian Evaluation Society Conference
“Evalueringskultur i en kompleks verden”

2021-10-21

Gustav Jakob Petersson
gustav.j.petersson@gmail.com


Cyber Society
Big Data
and
Evaluation
Comparative Policy Evaluation
Volume 24
Gustav Jakob Petersson and
Jonathan D. Breul, editors

JAN 2017

GLOBAL DIGITAL SNAPSHOT

KEY STATISTICAL INDICATORS FOR THE WORLD'S INTERNET, MOBILE, AND SOCIAL MEDIA USERS

TOTAL POPULATION	INTERNET USERS	ACTIVE SOCIAL MEDIA USERS	UNIQUE MOBILE USERS	ACTIVE MOBILE SOCIAL USERS
7.476 BILLION	3.773 BILLION	2.789 BILLION	4.917 BILLION	2.549 BILLION
URBANISATION: 54%	PENETRATION: 50%	PENETRATION: 37%	PENETRATION: 66%	PENETRATION: 34%

SOURCES: POPULATION: UNITED NATIONS; U.S. CENSUS BUREAU; INTERNET: INTERNETWORLDSTATS; ITU; INTERNETLIVESTATS; CIA WORLD FACTBOOK; FACEBOOK; NATIONAL REGULATORY AUTHORITIES; SOCIAL MEDIA AND MOBILE SOCIAL MEDIA: FACEBOOK; TENCENT; VKONTAKTE; LIVEINTERNET.RU; KAKAO; NAVER; NIKI AGHAEI; CAFEBAZAAR; SIMILARWEB; DING; EXTRAPOLATION OF TNS DATA; MOBILE: GSMA INTELLIGENCE; EXTRAPOLATION OF EMARKETER AND ERICSSON DATA.

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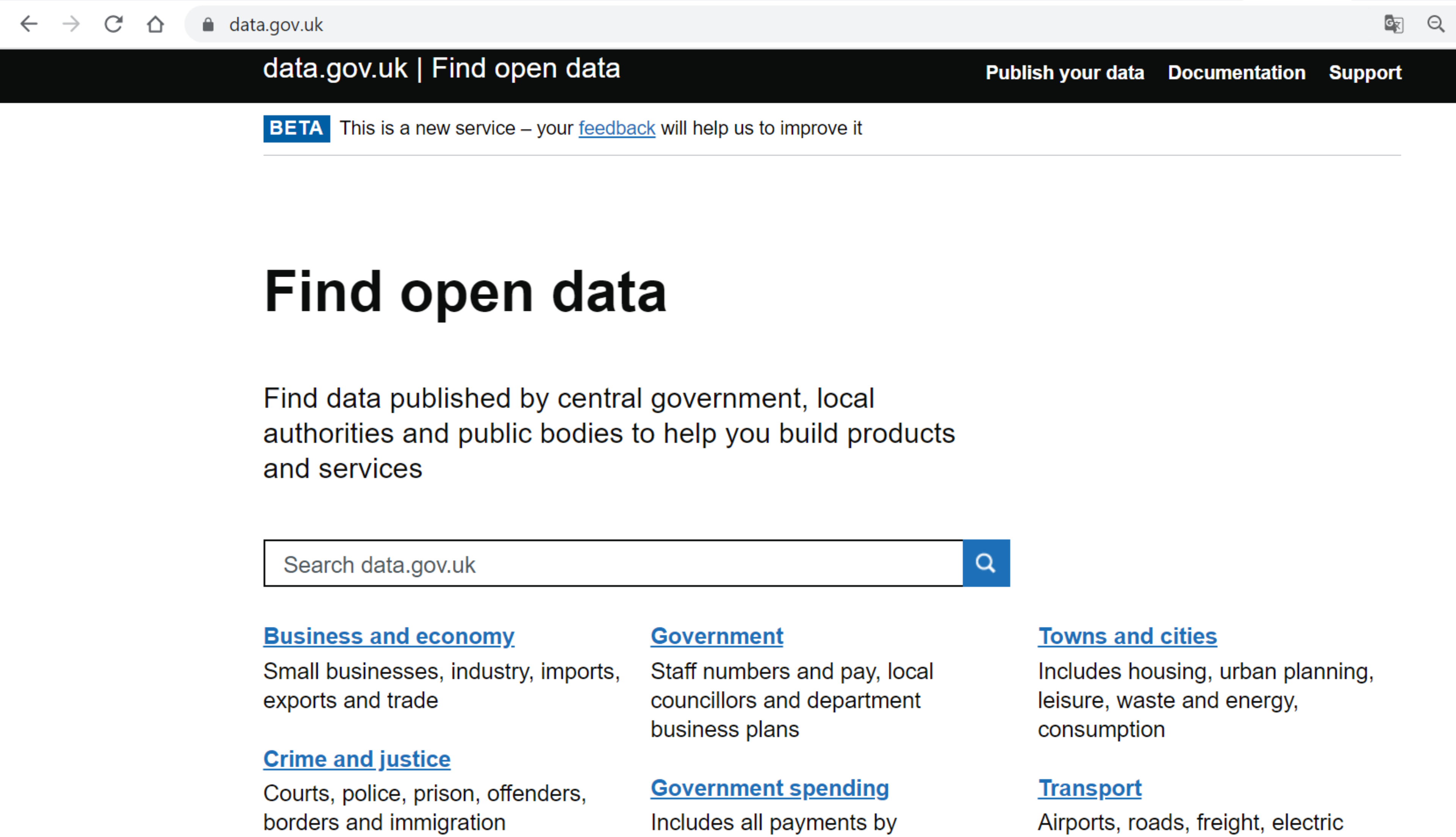
NASA Earth Science Data: Yours to Use, Fully and Without Restrictions

NASA's data policy ensures that all NASA data are available fully, openly, and without restrictions. Here's what this means for you.

Kevin Murphy, NASA Program Executive for Earth Science Data Systems

NASA data and data products exist for the purpose of furthering scientific research. In fact, a primary charge of NASA is ensuring that all data produced by NASA, including the code and algorithms used to produce these data, are available fully and openly to data users. This full and open data policy also ensures that there is no period of exclusive use of these data or access to these data, and that they are made available as soon as practical following the launch of a satellite or the start of a mission. NASA has been a leading advocate for providing full and open access to data and algorithms since the 1990s.

A key component of this effort is NASA's Earth Observing System Data and Information System (EOSDIS), which is responsible for processing, archiving, and disseminating NASA's vast collection of data from Earth observing satellite, airborne, and ground-based missions as well as socioeconomic data. EOSDIS currently provides access to more than 27.5 petabytes of archived data and more than 11,000 unique data products along with the metadata, algorithms, source code, and imagery associated with these products (see NASA's complete Earth science Data and Information Policy as defined by NASA's Earth Science Data Systems (ESDS) Program). More than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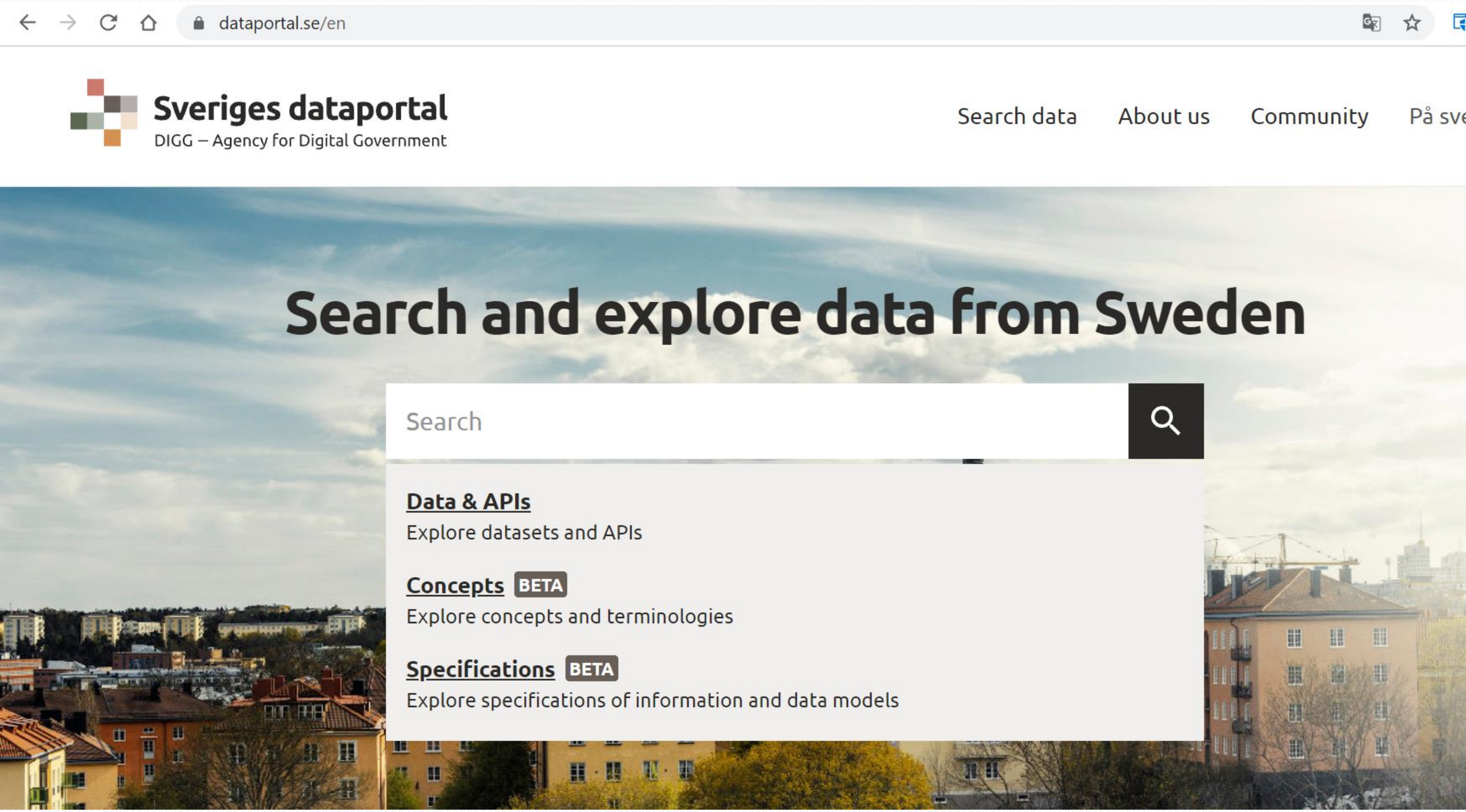
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Why "Big Data" Is a Big Deal

Information science promises to change the world.

by Jonathan Shaw

DATA NOW STREAM from daily life: from phones and credit cards and televisions and computers; from the infrastructure of cities; from sensor-equipped buildings, trains, buses, planes, bridges, and factories. The data flow so fast that the total accumulation of the past two years—a zettabyte—dwarfs the prior record of human civilization. "There is a big data revolution," says Weatherhead University Professor Gary King. But it is not the *quantity* of data that is revolutionary. "The big data revolution is that now we can *do* something with the data."

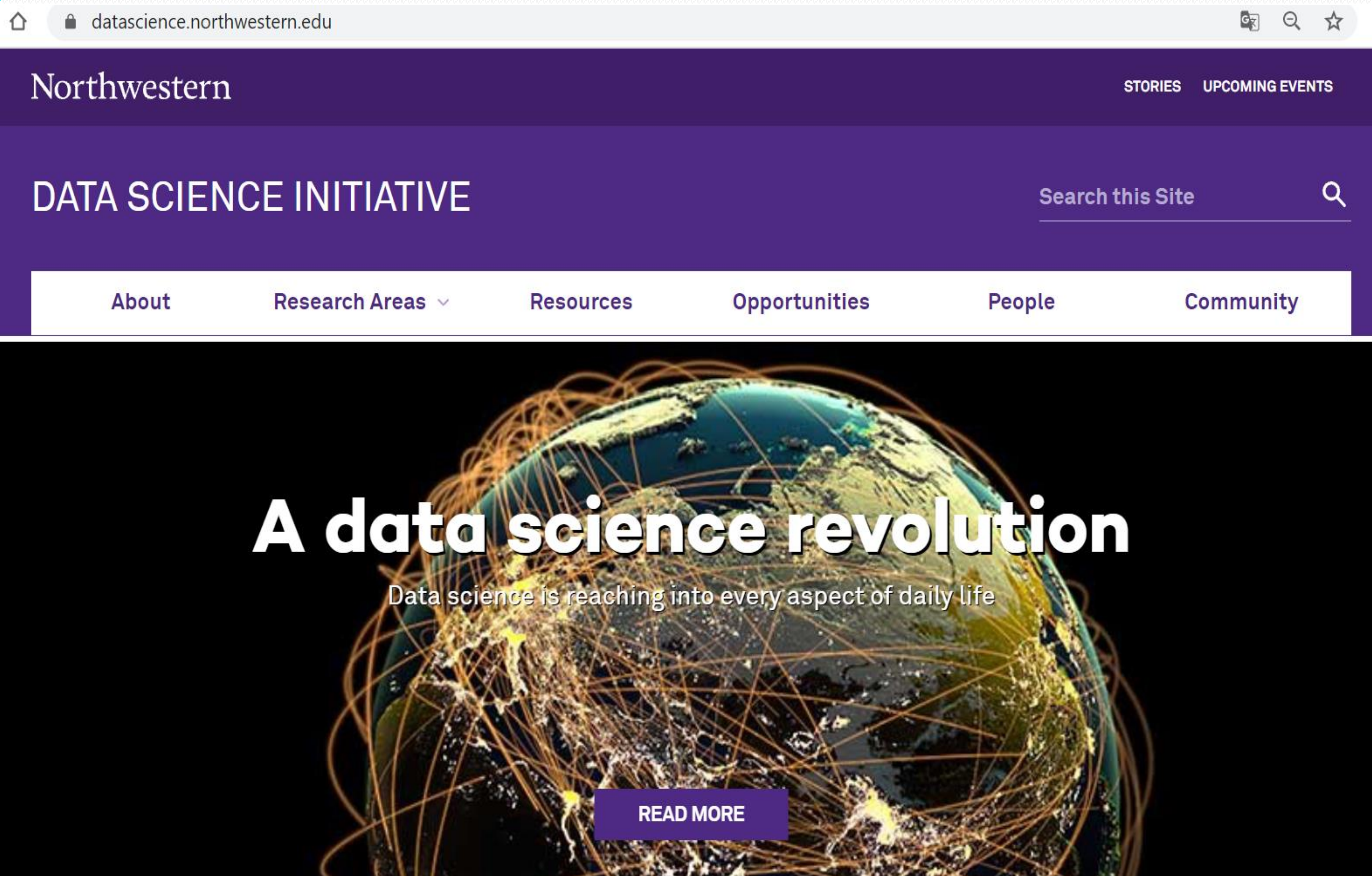
The revolution lies in improved statistical and computational methods, not in the exponential growth of storage or even computational capacity, King explains. The doubling of computing power every 18 months (Moore's Law) "is nothing compared to a big algorithm"—a set of rules that can be used to solve a problem a thousand times faster than conventional computational methods could. One colleague, faced with a mountain of data, figured out that he would need a $2-million computer to analyze it. Instead, King and his graduate students came up with an algorithm within two hours that would do the same thing in 20 minutes—on a laptop: a simple example, but illustrative.

New ways of *linking* datasets have played a large role in generating new insights. And creative approaches to *visualizing* data—humans are far better than computers at seeing patterns—frequently prove integral to the process of creating knowledge. Many of the tools now being developed can be used across disciplines as seemingly disparate as astronomy and medicine. Among students, there is a huge appetite for the new field. A Harvard course in data science last fall attracted 400 students, from the schools of law, business, government, design, and medicine, as well from the College, the School of Engineering and Applied Sciences (SEAS), and even MIT. Faculty members have taken note: the Harvard School of Public Health (HSPH) will introduce a new master's program in computational biology and quantitative genetics next year, likely a precursor to a Ph.D. program. In SEAS, there is talk of organizing a master's in data science.

"There is a movement of quantification rumbling across fields in academia and science, industry and government and nonprofits," says King, who directs Harvard's Institute for Quantitative Social Science (IQSS), a hub of expertise for interdisciplinary projects aimed at solving problems in human society. Among faculty colleagues, he reports, "Half the members of the government department are doing some type of data analysis, along with much of the sociology department and a good fraction of economics, more than half of the School of Public Health, and a lot in the Medical School." Even law has been seized by the movement to empirical research—"which is social science," he says. "It is hard to find an area that hasn't been affected."

The story follows a similar pattern in every field, King asserts. The leaders are qualitative experts in their field. Then a statistical researcher who doesn't know the details of the field comes in and, using modern data analysis, adds tremendous insight and value. As an example, he describes how Kevin Quinn, formerly an assistant professor of government at Harvard, ran a contest comparing his statistical model to the qualitative judgments of 87 law professors to see which could best predict the outcome of all the Supreme Court cases in a year. "The law professors knew the jurisprudence and what each of the justices had decided in previous cases, they knew the case law and all the arguments," King recalls. "Quinn and his collaborator, Andrew Martin [then an associate professor of political science at Washington University], collected six crude variables on a whole lot of previous cases and did an analysis." King pauses a moment. "I think you know how this is going to end. It was no contest." Whenever sufficient information can be quantified, modern statistical methods will outperform an individual or small group of people every time.

In marketing, familiar uses of big data include "recommendation engines" like those used by companies such as Netflix and Amazon to make purchase suggestions based on the prior interests of one customer as compared to millions of others. Target famously (or infamously) used an algorithm to detect when women were pregnant by tracking purchases of items such as unscented lotions—and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Big Data & Society (BD&S) is an Open Access peer-reviewed scholarly journal that publishes interdisciplinary work principally in the social sciences, humanities and computing and their intersections with the arts and natural sciences about the implications of Big Data for societies.

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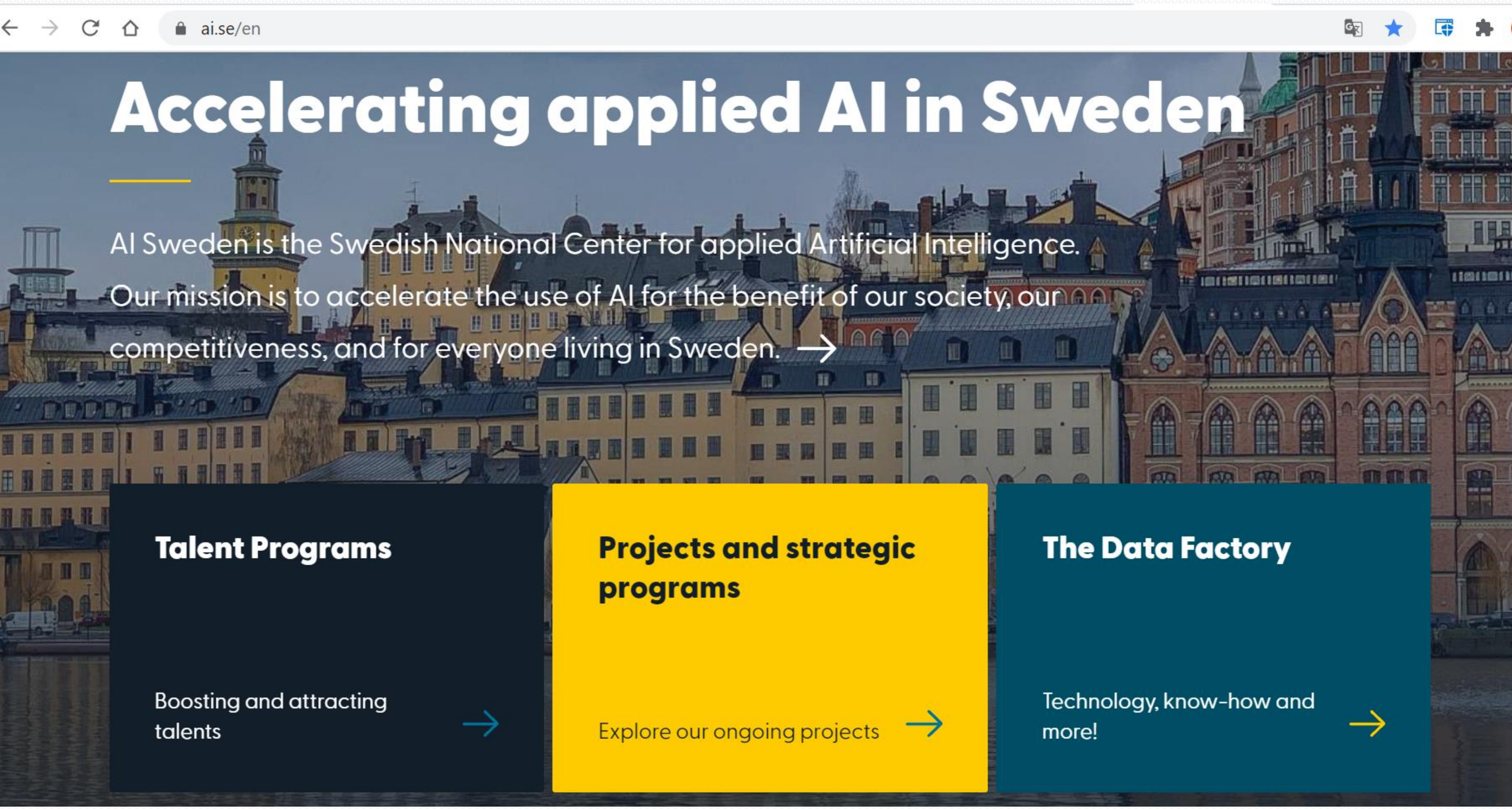
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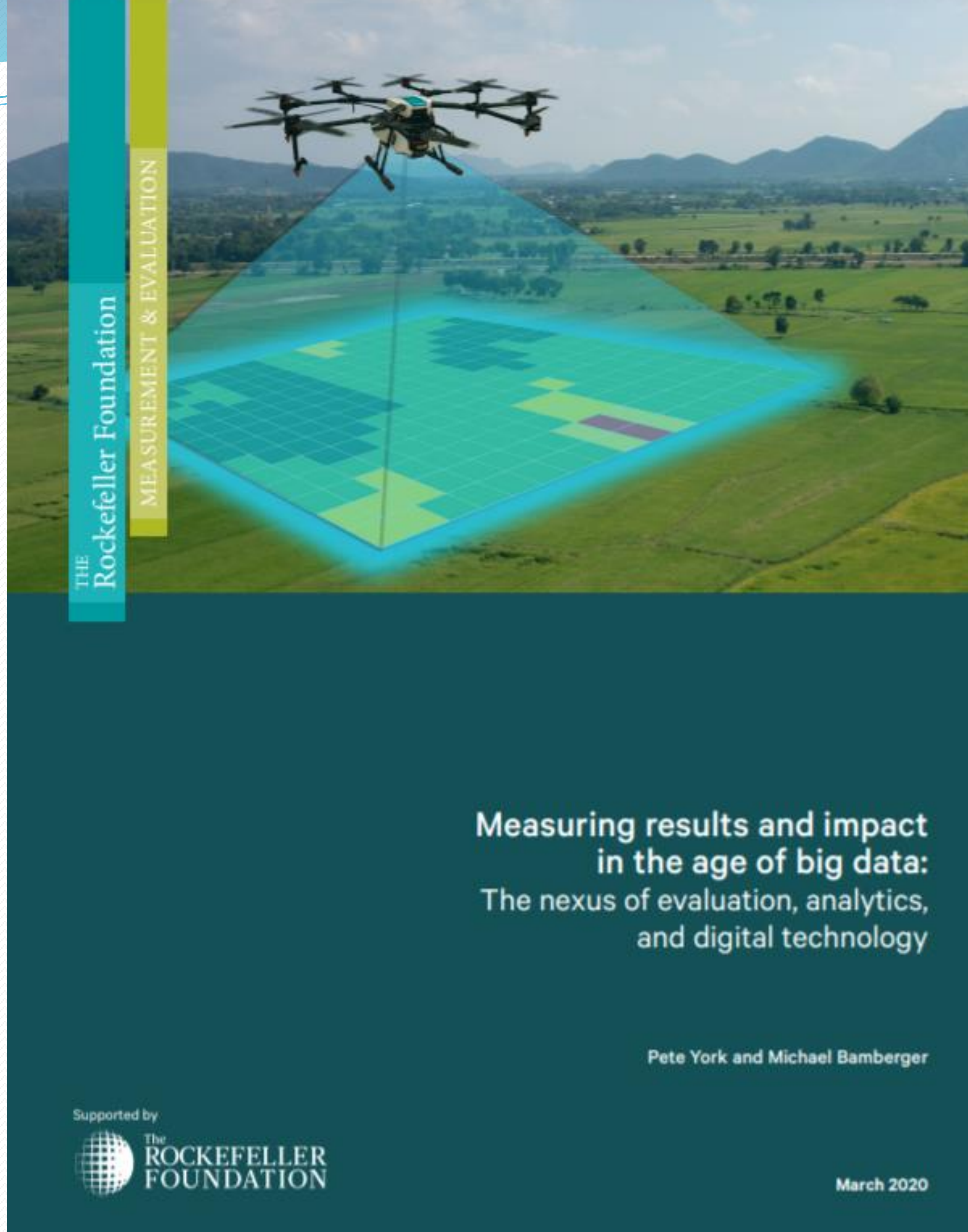
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MEASUREMENT & EVALUATION
Measuring results and impact in the age of big data:
The nexus of evaluation, analytics, and digital technology
Pete York and Michael Bamberger
Supported by
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March 2020

Today:

- Which are the advantages of using Big Data in evaluation?
- What can evaluation give in return?
- Which challenges must be met to achieve more collaboration?

Big Data?

- IT organizations are experiencing growing needs for storage capacity, performance, functionality and flexibility that is reaching a breaking point for traditional storage approaches. Big data analytics, mobility and social platform integration have become an everyday requirement. (IBM)
- These data are also unique because they are "naturally occurring," unlike survey data which result from the intrusion of researchers into everyday life. (Bail 2014, p. 469)

Is Big Data more than data?

"We define Big Data as a cultural, technological, and scholarly phenomenon that rests on the interplay of:

1. Technology: maximizing computation power and algorithmic accuracy to gather, analyze, link, and compare large data sets.
2. Analysis: drawing on large data sets to identify patterns in order to make economic, social, technical, and legal claims.
3. Mythology: the widespread belief that large data sets offer a higher form of intelligence and knowledge that can generate insights that were previously impossible, with the aura of truth, objectivity, and accuracy."

   - Boyd and Crawford (2012: 663)

Big Data in evaluation?

- Data sources traditionally not used in evaluation (ex. some automatically generated)
- Digitalized records (ex. combined administrative records)
- New analytics (AI, machine learning, data science…)
  - Data does not have to be strictly organized

Why Big Data in evaluation?

- There are calls for:
  - Ex ante: Quicker delivery of results (RTE etc.)
  - Ex post : More generalizable evidence (metaanalysis etc.): Campbell Collaboration, EPPI, 3ie

- Big Data can offer:
  - Real-time data
  - Predictive modelling
  - Larger data sets
  - Potentially powerful statistical analyses (precision)

Why Big Data in evaluation?

- Design challenges:
  - Defining a counterfactual
  - Identifying unintended outcomes
- Data challenges:
  - Mirror difficult-to-study phenomena
  - Cost of data collection
  - Sample selection bias
- Dissemination of results:
  - Data visualization
- Competition…

EVALUATION DEPARTMENT

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A Trusted Facilitator:
An Evaluation of Norwegian Engagement in the Peace Process between the Colombian Government and the FARC, 2010–2016

CONTENT

Perspective

Meaningful measures of human society in the twenty-first century

https://doi.org/10.1038/s41586-021-03660-7

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Published online: 30 June 2021

Check for updates

David Lazer[1,2✉], Eszter Hargittai[3], Deen Freelon[4], Sandra Gonzalez-Bailon[5], Kevin Munger[6], Katherine Ognyanova[7] & Jason Radford[1]

Science rarely proceeds beyond what scientists can observe and measure, and sometimes what can be observed proceeds far ahead of scientific understanding. The twenty-first century offers such a moment in the study of human societies. A vastly larger share of behaviours is observed today than would have been imaginable at the close of the twentieth century. Our interpersonal communication, our movements and many of our everyday actions, are all potentially accessible for scientific research; sometimes through purposive instrumentation for scientific objectives (for example, satellite imagery), but far more often these objectives are, literally, an afterthought (for example, Twitter data streams). Here we evaluate the potential of this massive instrumentation—the creation of techniques for the structured representation and quantification—of human behaviour through the lens of scientific measurement and its principles. In particular, we focus on the question of how we extract scientific meaning from data that often were not created for such purposes. These data present conceptual, computational and ethical challenges that require a rejuvenation of our scientific theories to keep up with the rapidly changing social realities and our capacities to capture them. We require, in other words, new approaches to manage, use and analyse data.

Sensor technologies have multiplied across many realms of human activity, from tracking devices in cars to online browsing. Satellites scan and digitize the planet at regular intervals. The development of techniques for processing unstructured data such as text, images, audio and video by computer scientists animates the conversion of—for example—books[1], radio broadcasts[2] and television shows[3] into data. In the twenty-first century, human behaviour—from mobility to information consumption to various types of interpersonal communication—is increasingly recorded somewhere and potentially computationally tractable. Past communication technologies, from mail to print to fax, typically left far fewer durable and accessible artefacts; those that did have become computationally accessible only in the past decade or so, as the relevant physical artefacts were digitized. The digitization of books is an example, which enables the computational analysis of a massive corpus of human expression that stretches back centuries[4].

The emergence of these new data streams has often been compared to the development of the telescope. As Robert Merton famously wrote, "Perhaps sociology is not yet ready for its Einstein because it has not yet found its Kepler....'[5]. Merton's provocation was that sociology did not yet have the empirical foundations on which to build great theory. Duncan Watts, in response, writes 62 years later, "...by rendering the unmeasurable measurable, the technological revolution in mobile, Web, and Internet communications has the potential to revolutionize our understanding of ourselves and how we interact. Merton was right: social science still has not found its Kepler. But three hundred years after Alexander Pope argued that the proper study of mankind should lie not in the heavens but in ourselves, we have finally found our telescope."[6].

We believe in the potential of digital data sources to transform the social sciences. However, the metaphor of the data streams from the instrumented society as a 'telescope' is misleading in important ways. First, the study of societies is different from the study of the stars, because the patterns that characterize human behaviour will generally differ across time and place. Second, the measures built from these streams are potentially suspect in ways that must be actively interrogated, because these sources were not built with scientific goals in mind. We now turn to the first point; the remainder of the paper is devoted to the second.

The unstable logics of society and measurement

Empirical social science is largely focused on finding generalizable but not universal patterns in human behaviour. The part of the social sciences that has the intent of finding such universal patterns in human behaviour (for example, evolutionary psychology) is tiny relative to the whole field. The issue of the instability of the rules that govern human society is exacerbated by the very sociotechnical systems that are gathering the data about people, which are actively (and in some cases intentionally) changing the social world that social science would study. Through what social scientists call reflexivity and self-fulfilling prophecies, humans actively change the world that they are observing

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Technologies to generate supplementary data

- Social Media Survey Apps (Bail 2015):
  - request permission to access public and nonpublic data from users of an organization's social media page and
  - distribute a survey among the users to capture additional data of interest to a researcher.

eba.se/en/reports/geospatial-analysis-of-aid-a-new-approach-to-aid-evaluation/6435/

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Reports

2017 | Evaluation of Aid | Description of method

Geospatial Analysis of Aid: A New Approach to Aid Evaluation

Ann-Sofie Isaksson

Recent years have seen an increased focus on results in development cooperation, and a heated debate on the evaluation strategies and effectiveness of development policies. A rapid expansion in the availability of sub-nationally georeferenced data on aid interventions as well as of geocoded data on relevant outcomes and covariates of aid opens for new possibilities in terms of aid evaluation.

Independent Office of Evaluation

IFAD
Investing in rural people

Georgia
Agricultural Support Project

IMPACT EVALUATION

IFAD 2017, Report No. 4537-GE

Forest Monitoring for Action (FORMA)

Forest Monitoring for Action (FORMA) uses satellite data to generate regularly updated online maps and alerts of tropical forest clearing. David Wheeler, now a CGD senior fellow emeritus, assembled and led a small team that created FORMA, which has since become a core component of the World Resources Institute (WRI) Global Forest Monitoring (GFW) platform launched in February 2014.

FORMA is now available for visualization, analysis, and download at GFW, a dynamic online forest monitoring and alert system that empowers people everywhere to better manage forests. CGD continues to work closely with WRI on forest monitoring issues as part of our Forests for Climate and Development initiative.

Using current data accessed via GFW, FORMA can be used to support international efforts to curb greenhouse gas emissions by demonstrating to those willing to pay for forest conservation (for example, through the Forest Carbon Partnership Facility (FCPF), bilateral programs such as Norway's Forest and Climate Initiative or UN-REDD) that protected forests are indeed still standing. CGD has developed the Forest Conservation Performance Rating (fCPR) system as a set of benchmarks that showcase global progress in reducing forest clearing and that could form the basis for such payments.

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Data Science Methods in Development Evaluation: Exploring the Potential

Gustav Engström, Jonas Norén

This report examines the potential of using data science and Natural Language Processing (NLP) in development evaluation. It looks at how such methods can be used produce reliable assessments of what past evaluations have concluded about aid projects and programmes (relating to OECD/DAC's evaluation criteria relevance). It also discusses the strengths and weaknesses of these methods compared to approaches relying on manual techniques.

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KB tillgängliggör kraftfulla modeller för språkförståelse

4 februari 2020

Forskning

I dag publicerar KB tre svenska språkmodeller baserade på Googles "BERT" (Bidirectional Encoder Representations from Transformers). De första testerna visar att KB:s modeller överträffar Googles flerspråkiga modell.

En språkförståelsemodell är ett omfattande artificiellt neuralt nätverk som tränats på

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Data Readiness for Natural Language Processing

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Abstract

This document concerns data readiness in the context of machine learning and Natural Language Processing. It describes how an organization may proceed to identify, make available, validate, and prepare data to facilitate automated analysis methods. The contents of the document is based on the practical challenges and frequently asked questions we have encountered in our work as an applied research institute with helping organizations and companies, both in the public and private sectors, to use data in their business processes.

1 Introduction

At the Research Institutes of Sweden (RISE)[1], we work in cooperation with other organizations and companies, both in the public and private sectors, with research and innovation in Natural Language Processing (NLP). A major challenge that we often encounter is a lack of readiness with respect to data. Even if the research problem is sufficiently well defined, and the business value of the proposed solution is well described, it is often not clear what type of data is required, if it is available, or if it at all exists. We find that there is often not even a framework available to discuss issues related to data. The purpose of this document is to outline and highlight issues related to data accessibility, validity, and utility that may arise in such situations. We hope that this document may serve as a guide for working practically with data in the context of applied NLP.

1.1 Scope

This document is concerned exclusively with data readiness in the context of NLP. Other modalities such as images, video, or sensor data are not covered, but similar considerations apply in those cases.

Work on data readiness related to other forms of data include that of Nazabal et al. (2020), who address data wrangling issues from a general stand-point using a set of case studies, as well as the work by van Ooijen (2019), and Harvey and Glocker (2019) that both deal with data quality in medical imaging. We have not found any work that focuses specifically on data readiness in the context of NLP.

1.2 How to use this document

The intention is for this document to provide insights into the type of challenges one might encounter, with respect to data, when embarking on a project involving NLP. The document is focused on asking the right questions rather than providing an explicit guide that covers all possible challenges in a project: such a guiding will inevitably vary with the specific task at hand. The following four sections make up the document:

- *Data Readiness Levels* introduce the notion of data readiness.
- *Project phases* outlines the typical structure of a research or innovation project, and puts data readiness into context within that structure.

[1] https://ri.se

Why evaluation in Big Data?

DOI:10.1145/3132698

Hanna Wallach

Viewpoint

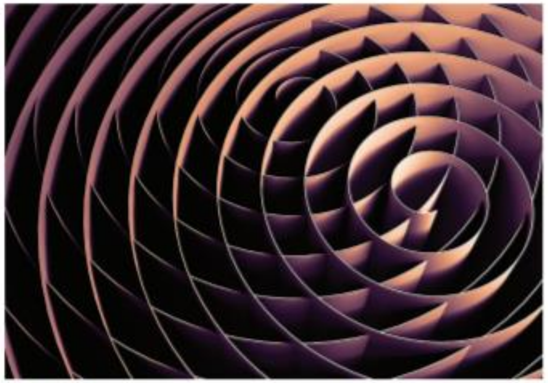
Computational Social Science ≠ Computer Science + Social Data

The important intersection of computer science and social science.

THIS VIEWPOINT IS about differences between computer science and social science, and their implications for *computational* social science. Spoiler alert: The punchline is simple. Despite all the hype, machine learning is not a be-all and end-all solution. We still need social scientists if we are going to use machine learning to study social phenomena in a responsible and ethical manner.

I am a machine learning researcher by training. That said, my recent work has been pretty far from traditional machine learning. Instead, my focus has been on computational social science—the study of social phenomena using digitized information and computational and statistical methods.

For example, imagine you want to know how much activity on websites such as Amazon or Netflix is caused by recommendations versus other factors. To answer this question, you might develop a statistical model for estimating causal effects from observational data such as the numbers of recommendation-based visits and numbers of total visits to individual product or movie pages over time.[8]



Alternatively, imagine you are interested in explaining when and why senators' voting patterns on particular issues deviate from what would be expected from their party affiliations and ideologies. To answer this question, you might model a set of issue-based adjustments to each senator's ideological position using their congressional voting history and the corresponding bill text.[4,9]

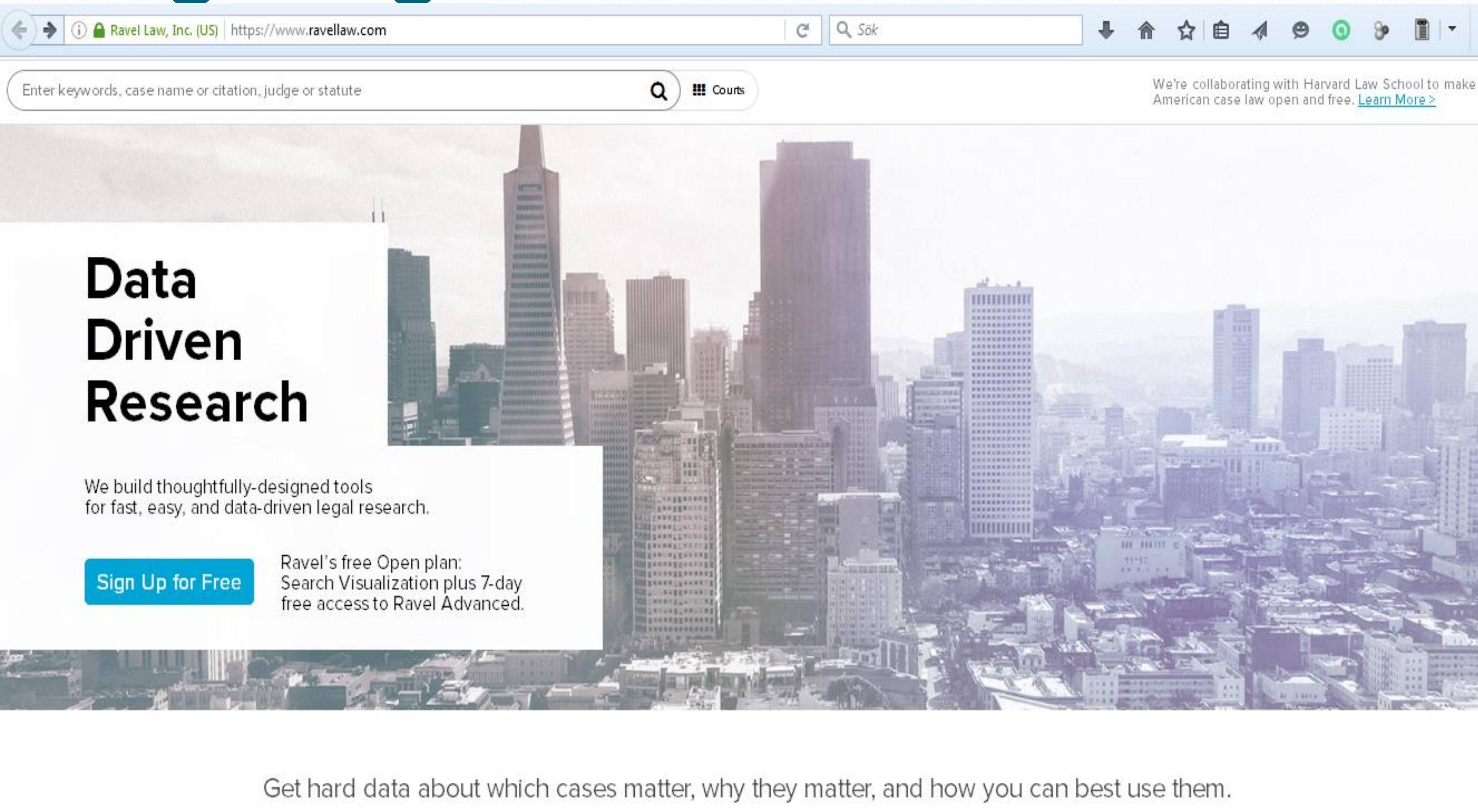
Finally, imagine you want to study the faculty hiring system in the U.S. to determine whether there is evidence of a hierarchy reflective of systematic social inequality. Here, you might model the dynamics of hiring relationships between universities over time using the placements of thousands of tenure-track faculty.[3]

Unsurprisingly, tackling these kinds of questions requires an interdisciplinary approach—and, indeed, computational social science sits at the intersection of computer science, statistics, and social science.

For me, shifting away from traditional machine learning and into this interdisciplinary space has meant that I have needed to think outside the algorithmic black boxes often associated with machine learning, focusing instead on the opportunities and challenges involved in developing and using machine learning methods to analyze real-world data about society.

This Viewpoint constitutes a reflection on these opportunities and challenges. I structure my discussion here

Legal Big Data



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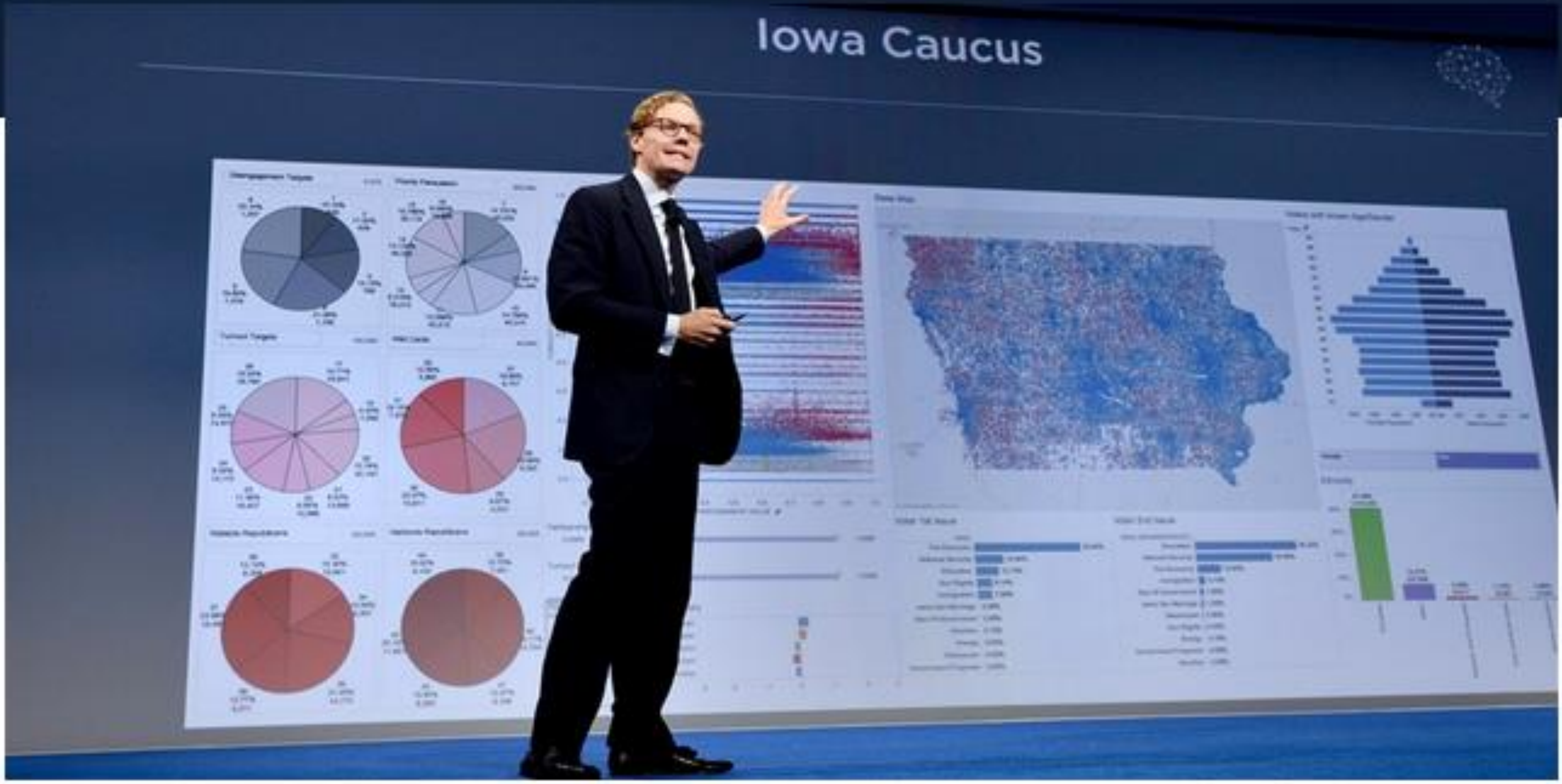
by Phil McCausland and Anna R. Schecter / Mar.17.2018 / 8:40 PM ET / Updated Mar.18.2018 / 12:50 AM ET



CEO of Cambridge Analytica Alexander Nix speaks at the 2016 Concordia Summit - Day 1 at the Grand Hyatt New York on Sep. 19, 2016 in New York City. Bryan Bedder / Getty Images for Concordia Summit

Mark Zuckerberg's Reckoning: 'This Is a Major Trust Issue'

Leer en español

By KEVIN ROOSE and SHEERA FRENKEL MARCH 21, 2018

99

"Whenever there's an issue where someone's data gets passed to someone who the rules of the system shouldn't have allowed it to, that's rightfully a big issue and deserves to be a big uproar," Mark Zuckerberg, Facebook's chief executive, said in an interview. David Paul Morris/Bloomberg

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Apple Fights Order to Unlock San Bernardino Shooter's iPhone

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Apple is fiercely opposing a court order to unlock the iPhone used by one of the San Bernardino shooters, accusing the federal government of an "overreach" that could potentially breach the privacy of millions of customers.

CEO Tim Cook published a bullish open letter late Tuesday, pledging to fight a judge's ruling that it should give FBI investigators access to encrypted data on the device.

"The government is asking Apple to hack our own users and undermine decades of security advancements that protect our customers — including tens of millions of American citizens — from sophisticated hackers and cybercriminals," Cook wrote, calling the ruling a "dangerous

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THE END OF THEORY: THE DATA DELUGE MAKES THE SCIENTIFIC METHOD OBSOLETE

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Illustration: Marian Bantjes

Correlation vs. causation

”Correlation supersedes causation, and science can advance even without coherent models, unified theories, or really any mechanistic explanation at all. There’s no reason to cling to our old ways” (Anderson 2008)

4 misconceptions about Big Data

(Lemire – Petersson 2017)

1. A shift from *theory* to *data-driven* knowledge production
2. A shift from *causation* to *correlation*
3. A shift from *samples* to *total populations* (n=All)
4. A shift from *clean* to *messy* data

Simpson’s paradox

- Is a frequently cited reason why causation cannot be reduced to correlation
- Morris Cohen and Ernst Nagel (1910) studied death frequencies for tuberculosis. Death rates…

1. For afro americans: lower in Richmond than in New York.
2. For caucasians: lower in Richmond than in New York.
3. For afro americans *and* caucasians: *higher* in Richmond than in New York.

Google flu trends revisited …

- In 2008: most accurate predictions
- But difficult to repeat this success
  - Algorithm dynamics? (Lazer et al., 2014)
  - Changes in the knowledge base of users?

Objectives in RBM and evaluation?

- We wish to influence reality:
  - Not correlations – but mechanisms: the responses of individuals
  - Which parts of a program activate mechanisms?
  - Would another program activate the same mechanisms?

- Again – we will need theory!


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”Digital smoke signals”: theory!

The invisible descent into poverty:

1. Additional income, reduced expenses, help from family and friends
2. Spending of savings, new debts, sell property
3. Children are not sent to school etc.

Evaluator competencies

- Identifying informational needs
- Understanding theories of the intervention: ToC etc.
- Utilizing social scientific theory
- Utilizing causality theories (design)
- Managing primary data: Big Data + Small Data
- Estimating validity and reliability risks : Construct validity potentially increasingly important

Evaluator competencies

- Ethical concerns
- Making value judgements
- Making sure results are used: ”People, people and people”
- Etc.!

Conclusion: There are important synergies!

Challenges: evaluators

- Learn about new designs and tools
- Update statistical skills
- Broaden our role in the policy process: Ex-ante discussions
- Update our ethical guidelines?
- Market our strengths!

Challenges: updated ecosystem

- Academic training that combines Big Data and evaluation approaches and methods
- Funding for collaborative research
- Organizational structures in government agencies that facilitate cooperation and convergence
- Open data access for all sectors
- Data sharing partnerships
- Federated learning (GDPR)

Challenges: managers

- Realise complementarities
- Build joint teams for evaluative inquiry (not separate departments)
  - Helps form a common language!
- Data sharing partnerships
- Data readiness – Outsourcing of analytics?

Challenges: commissioners

- Realise complementarities
- Enhance collaboration and convergence through ToRs

Forss – Norén (2017):

- studied 25 ToRs from international development agencies
- 75% contained detailed prescriptions for design and data collection – frequently closing the door for Big Data.

Summarizing words

- The public sector has much to gain from collaboration between the evaluation and Big Data communities
- Evaluators have much to learn – and much to give
- We need an ecosystem that enhances collaboration and convergence, regarding for instance:
    - academic training
    - research funding
    - organizational structures
    - commissioning practices

Thanks for listening!

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