Outmaneuvering Complexity in Worlds of Surprise: Managing Fundamental Tradeoffs

David L. Alderson, PhD

Professor, Operations Research Department

Director, Center for Infrastructure Defense

Naval Postgraduate School

dlalders@nps.edu

Complexity Workshop: Advancing the State of Thought and Practice

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References and Acknowledgments

The ideas here are the result of longstanding collaborations:

- John Doyle (Caltech), Walter Willinger (Niksun), David Woods (Ohio State), Jerry Brown (NPS), Matt Carlyle (NPS), Tom Seager (ASU), Dan Eisenberg (NPS)

Selected References:

- D. Eisenberg, T. Seager, D. Alderson, 2019, “Rethinking Resilience Analytics,” Risk Analysis, https://doi.org/10.1111/risa.13328.
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Naval Postgraduate School (NPS)

America's national security research university

History Highlights

1909 Founded at U.S. Naval Academy

1951 Moved to Monterey, CA
Operations Research Curriculum

- Facilities of a graduate research university and a military base
- Faculty who work for the U.S. Navy, with clearances
- Mid-career students with fresh operational experience

2017:

- 65 M.S. and 15 Ph.D. programs
- 612 faculty
- 1432 resident students includes (166 international / 47 countries)
- 909 distributed learning students

What is Operations Research?

- Operations Research (OR) is the science of helping people and organizations make better decisions using
  - mathematical models, statistical analyses, simulations
  - analytical reasoning and common sense

  to the understanding and improvement of real-world operations.

Source: IDC/KDnuggets Advanced Analytics Survey, 2016

informs.

MORS
Military Operations Research Society

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  to the understanding and improvement of real-world operations.
- OR originated during World War II. The military uses OR at the strategic, operational, and tactical levels.
- Biggest users of OR: modern corporations.
- NPS has the oldest OR instructional program in existence.
- We conduct **analysis** and develop **decision support tools** that are of immediate operational relevance to the decision-maker.
- Often centered around Masters theses.

My Focus: Critical Infrastructure Systems

- ***Critical Infrastructure (CI)***: "systems and assets, whether physical or virtual, so vital to the United States that the incapacity or destruction of such systems and assets would have a debilitating impact on security, national economic security, national public health or safety, or any combination of those matters" ***--Section 1016(e) of the USA PATRIOT Act of 2001***











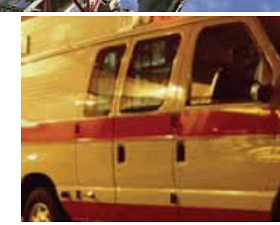

Network-Centric Infrastructure Systems
(a.k.a. Cyber-Physical-Social Systems)

- A mix of human and automated system operators to remotely monitor, manage, and control the physical world

- via the Internet and related communication systems

- These systems support the operation and management of modern society's most vital functions
  - delivery of economic goods and services
  - business processes
  - global financial markets
  - education
  - health care
  - government services
  - military operations

The **GOOD**

Network technology (interpreted broadly) has been wildly successful…

… yielding a "networked planet" for energy, food, information, goods and materials,…

The **BAD**

Network technology has been *too* successful…

… yielding a "networked planet" for good *and bad*…

… and creating vulnerabilities due to our dependence.

The **UGLY**

These network-centric systems

Largely deliver what we design them to do.

But fail because they create new problems that we *did not expect.*

Main Challenge: ~~Managing~~ Outmaneuvering Complexity

- Designers & operators of the next-generation network-centric systems need to understand and manage their growing complexity.

We know:

how to design, build, and deploy network-centric systems

Not so easy:

predict or control their collective behavior once deployed

When things fail…

they often do so cryptically and catastrophically.

An All-Too-Common Pattern

- *According to Pl*an, things appear to be going great.
- Getting better and better, or so it seems!
- Until it isn't. And then it's *bad*…
- And unclear how to respond.

Key Message #1

We need to study these patterns of complexity as empirical phenomena

- Need to understand these patterns
- Without getting caught up in all the ”noise”
- Otherwise you will get lost

Where we agree…

- Oversimple abstractions don't work (for long)
  - ✗ Linear systems with predictable cause-effect
  - ✗ Root-cause analysis (e.g., blame the human!)
  - ✗ Stationarity in time

Where it's noisy…

- What are the patterns?
- What drives them?
- What to do about them?

Where does complexity come from?

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A common answer:

Complexity comes from *increased system scale*

- number of components
- number and types of interactions (often hidden)

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How to make sense of complexity?

Answer #1: abstract the problem (in scale) to identify the few key parameters that drive the system

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Answer #2: study the network (at scale), network science!

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rooted in physics and mathematics

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What's missing: organization…

How to make sense of complexity?

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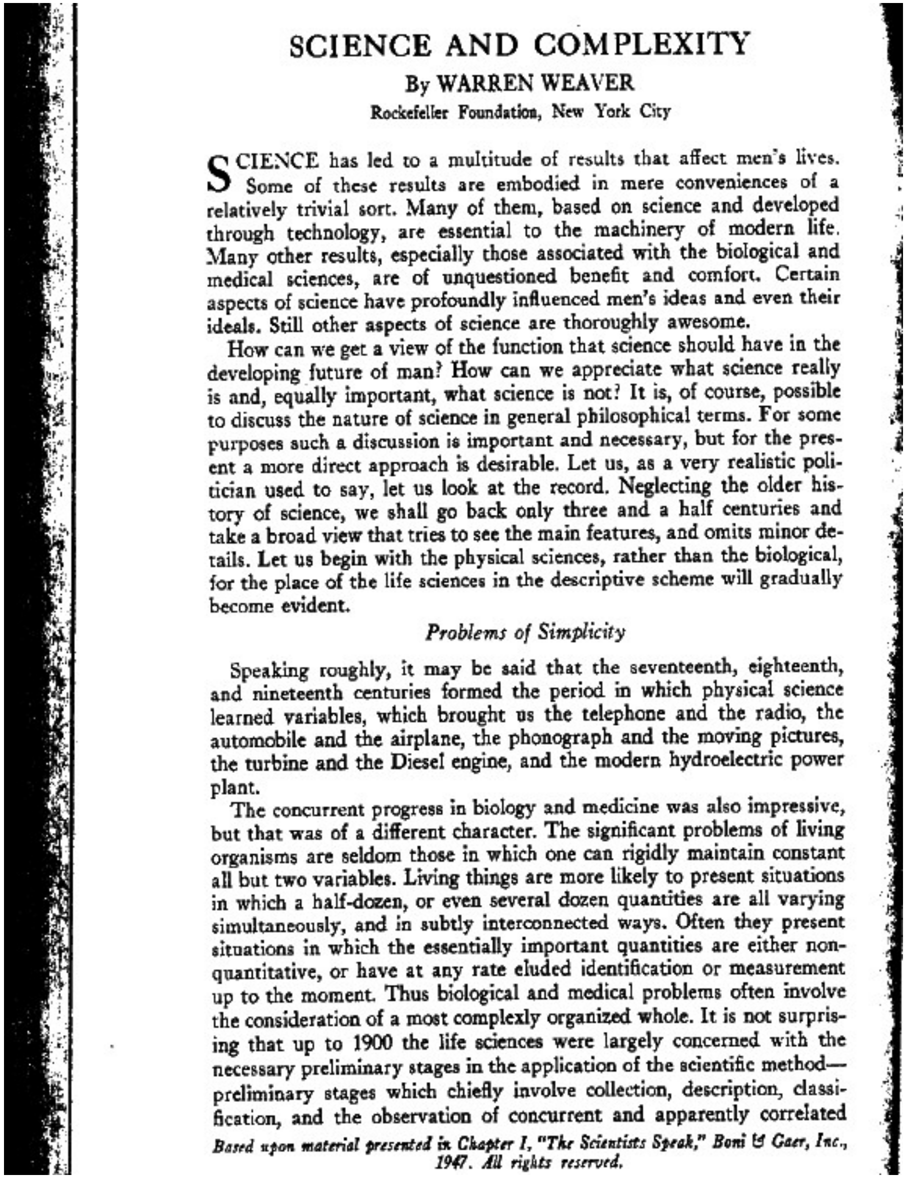


SCIENCE AND COMPLEXITY

By WARREN WEAVER

Rockefeller Foundation, New York City

SCIENCE has led to a multitude of results that affect men's lives. Some of these results are embodied in mere conveniences of a relatively trivial sort. Many of them, based on science and developed through technology, are essential to the machinery of modern life. Many other results, especially those associated with the biological and medical sciences, are of unquestioned benefit and comfort. Certain aspects of science have profoundly influenced men's ideas and even their ideals. Still other aspects of science are thoroughly awesome.

How can we get a view of the function that science should have in the developing future of man? How can we appreciate what science really is and, equally important, what science is not? It is, of course, possible to discuss the nature of science in general philosophical terms. For some purposes such a discussion is important and necessary, but for the present a more direct approach is desirable. Let us, as a very realistic politician used to say, let us look at the record. Neglecting the older history of science, we shall go back only three and a half centuries and take a broad view that tries to see the main features, and omits minor details. Let us begin with the physical sciences, rather than the biological, for the place of the life sciences in the descriptive scheme will gradually become evident.

Problems of Simplicity

Speaking roughly, it may be said that the seventeenth, eighteenth, and nineteenth centuries formed the period in which physical science learned variables, which brought us the telephone and the radio, the automobile and the airplane, the phonograph and the moving pictures, the turbine and the Diesel engine, and the modern hydroelectric power plant.

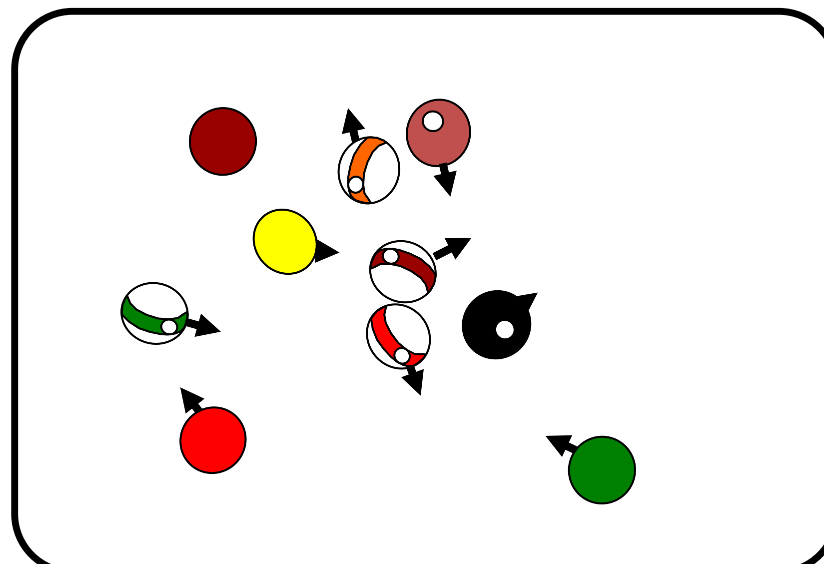
The concurrent progress in biology and medicine was also impressive, but that was of a different character. The significant problems of living organisms are seldom those in which one can rigidly maintain constant all but two variables. Living things are more likely to present situations in which a half-dozen, or even several dozen quantities are all varying simultaneously, and in subtly interconnected ways. Often they present situations in which the essentially important quantities are either non-quantitative, or have at any rate eluded identification or measurement up to the moment. Thus biological and medical problems often involve the consideration of a most complexly organized whole. It is not surprising that up to 1900 the life sciences were largely concerned with the necessary preliminary stages in the application of the scientific method—preliminary stages which chiefly involve collection, description, classification, and the observation of concurrent and apparently correlated

Based upon material presented in Chapter I, "The Scientists Speak," Boni & Gaer, Inc., 1947. All rights reserved.

"problems of simplicity" (Weaver 1948)

example: billiard balls

- **classical dynamics provide exact descriptions of a <u>small</u> number of balls interacting on a table**



Weaver, W. 1948. Science and complexity. American Scientist 36 536-544. Also available electronically from http://www.ceptualinstitute.com/genre/weaver/weaver-1947b.htm.

“disorganized complexity” (Weaver 1948)

- ***“The physical scientists, with the mathematicians often in the vanguard, developed powerful techniques of probability theory and of statistical mechanics to deal with what may be called problems of disorganized complexity.”***

- ***“The methods of statistical mechanics are valid only when the balls are distributed, in their positions and motions, in a helter-skelter, that is to say a disorganized, way.”***

1960s-Present: **disorganized complexity** + chaos, criticality, scale-free

Common features:

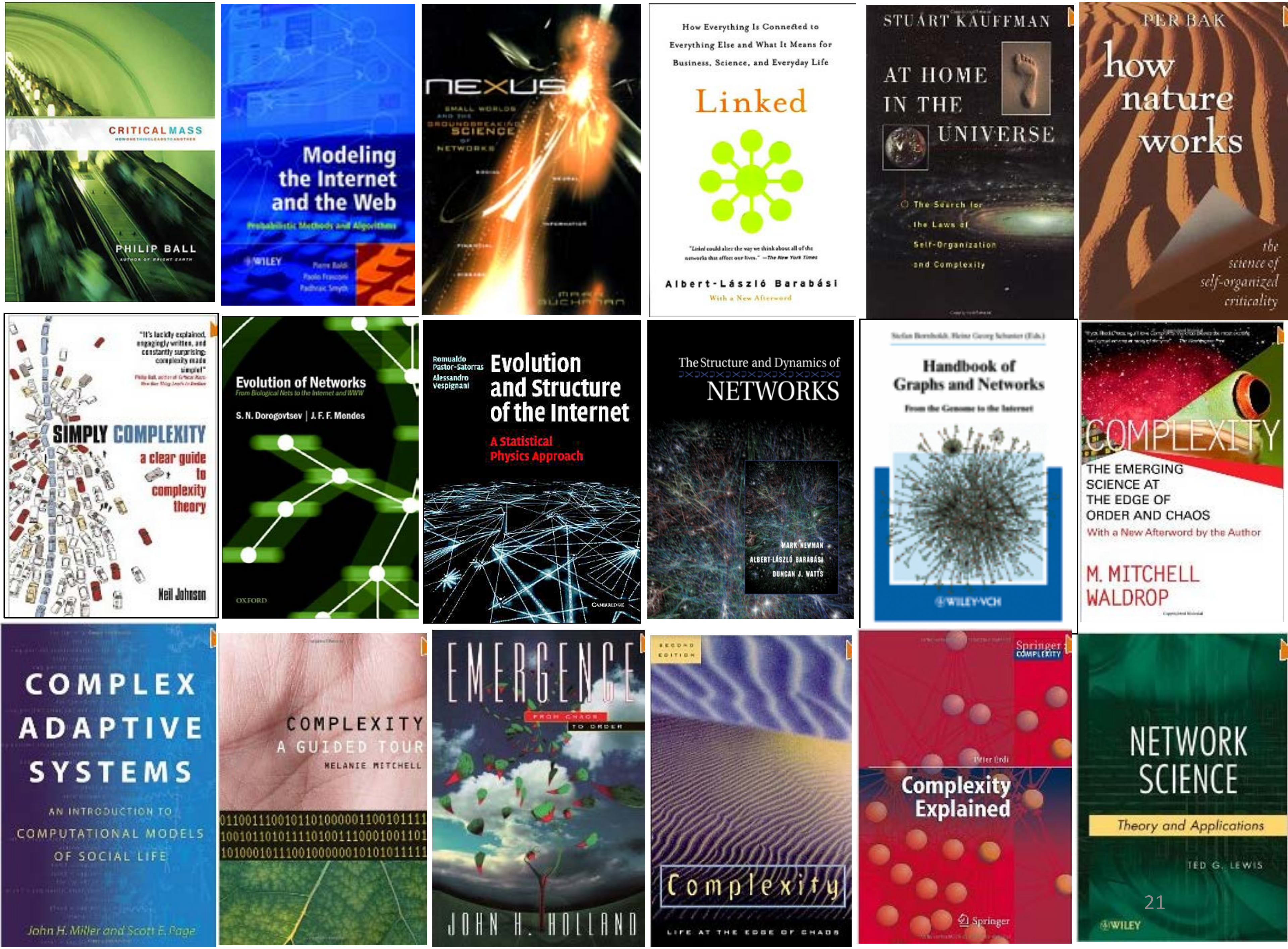
- Simple abstractions
- Universal appeal
- Celebrate emergence

Dominates today's scientific thinking about complexity

- Minimal role of:
  - constraints, tradeoffs
  - design

Features that arise from dis-organization:

- Unpredictabity
- Chaos, fractals
- Critical phase transitions
- Self-similarity
- Universality
- Pattern formation
- Edge-of-chaos
- Order for free
- Self-organized criticality
- Scale-free networks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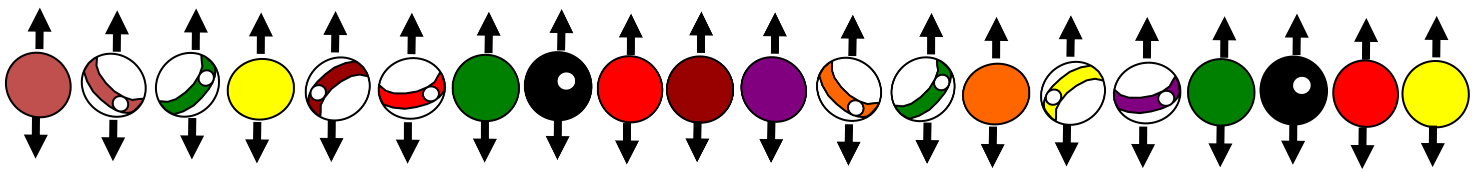
“organized complexity” (Weaver 1948)

- ***“For example, the statistical methods would not apply if someone were to arrange the balls in a row parallel to one side rail of the table, and then start them all moving in precisely parallel paths perpendicular to the row in which they stand. Then the balls would never collide with each other nor with two of the rails, and one would not have a situation of disorganized complexity."***



Systems exhibiting organized complexity:

- biological systems (Weaver)
- ecosystems
- economies
- social systems
- advanced technologies (e.g., network-centric systems)

organized complexity

- components are arranged in a very specialized way that enables functionality and/or robustness features
- even minimal random rearrangement of that structure tends to destroy its most salient features

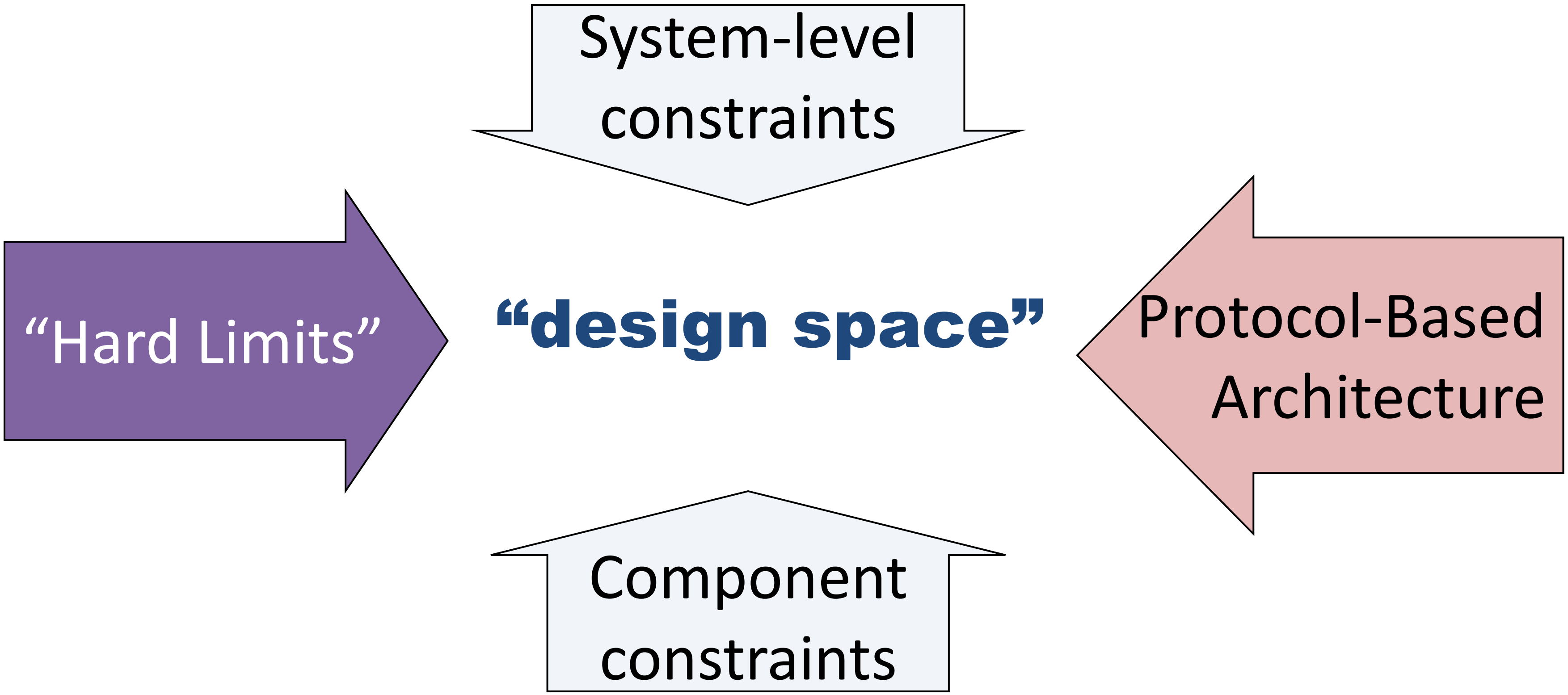
organized complexity

- components are arranged in a very specialized way that enables functionality and/or robustness features
- even minimal random rearrangement of that structure tends to destroy its most salient features

claim:

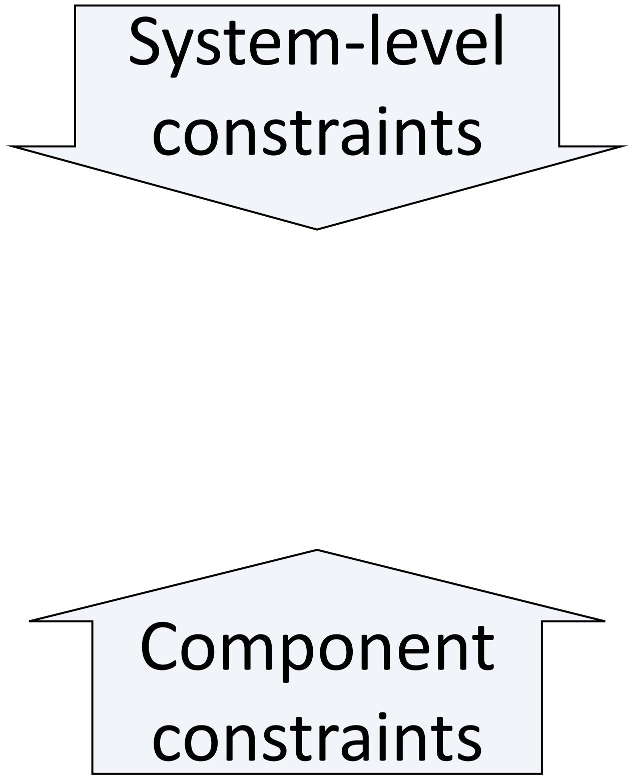
- *this structure is a consequence of specific constraints* that are placed on functionality and/or behavior
- largely independent of the process by which this organization arises, whether by *design* or *evolution*.

a constraint-based view of organized complexity



Fundamental claim: complex networks (that we care about) are the result of ***design*** (either evolution or engineering)

a constraint-based view of organized complexity



Constraints on the system as a whole (e.g., functional requirements)

Constraints on individual components (e.g., physical, energy, information)

“Hard Limits”

- ***Hard limits*** on system characteristics
  - ***implied by the intersection of component and system constraints***
- Most interesting when they do not follow trivially from the other constraints
- Examples:
  – Entropy/2nd law in thermodynamics
  – Channel capacity theorems in information theory
  – Bode integral and related limits in control theory
  – Undecidability, NP-hardness, etc in computational complexity theory

“Constraints that deconstrain”

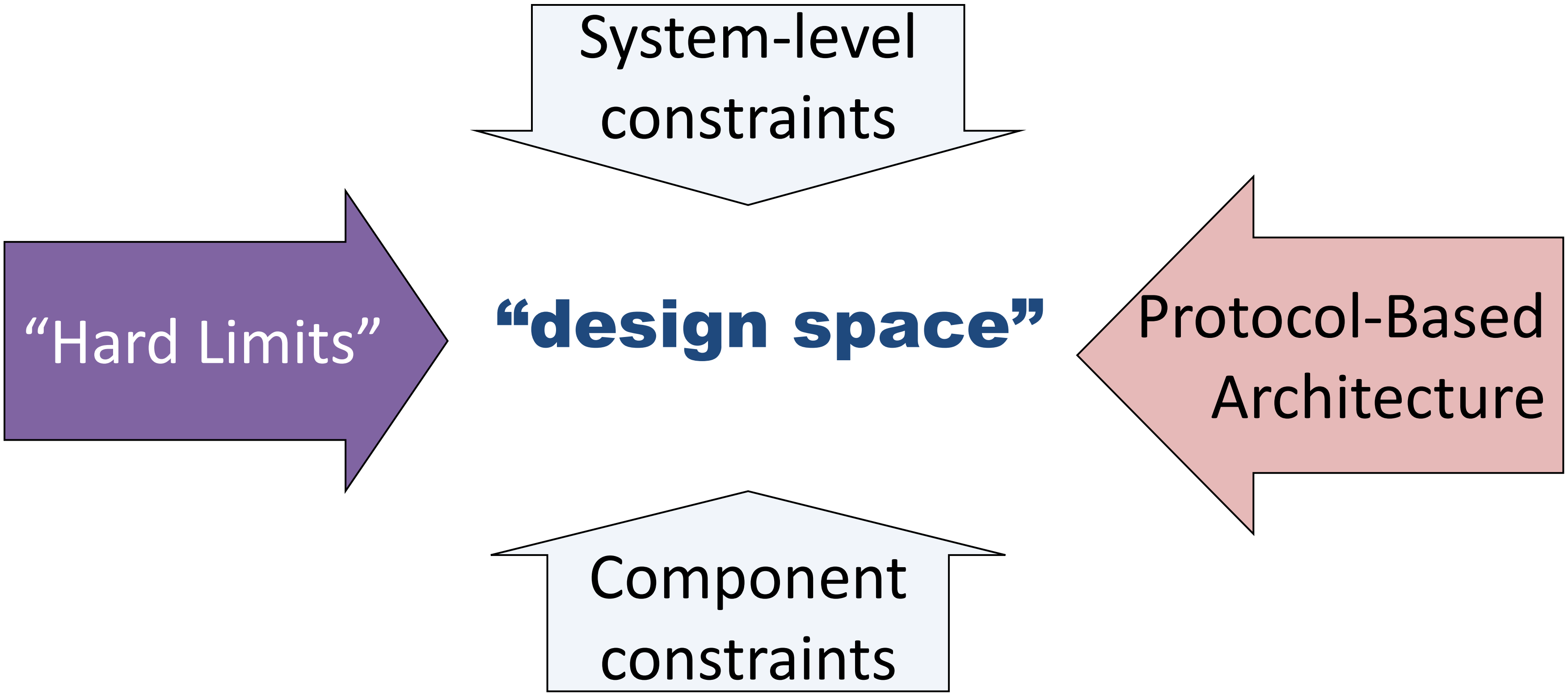
- Emphasis on *protocols*
  (persistent rules of interaction)
  over *modules*
  (that obey protocols and can change)

- In reverse engineering,
  - figure out what rules are being followed
  - and how they govern system features or behavior

- In forward engineering,
  - specify protocols that ensure such system behavior

Protocol-Based Architecture

a constraint-based view of organized complexity



REF: D. Alderson and J. Doyle, 2010, "Contrasting Views of Complexity and Their Implications for Network-Centric Infrastructures," *IEEE Transactions on Systems, Man, and Cybernetics-Part A* 40(4): 839-852.

The Need to Study Organized Complexity (Weaver 1948)

- *"Science must, over the next 50 years, learn to deal with these problems of organized complexity. Is there any promise on the horizon that this new advance can really be accomplished?*
- *. . . Out of [World War II] have come two new developments that may well be of major importance in helping science to solve these complex twentieth-century problems.*
- *The first piece of evidence is the wartime development of new types of electronic computing devices. . . .*
- *The second of the wartime advances is the 'mixed-team' approach of operations analysis."*

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Key Message #2

Is your system organized or disorganized?

How will you study its structure and function?

century problems.

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What's missing: organization…

How to make sense of complexity?

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How to make sense of complexity?

<u>Answer #3</u>: Organized complexity arises naturally in the <u>*adaptation*</u> of highly evolved systems

- from attempts to increase competitive advantage
- from <u>*attempts to increase system robustness*</u>

rooted in biology and engineering (especially control)

Robustness

Def: A [*property*] of [*a system*] is ***robust*** if it is [*invariant*] for [*a set of perturbations*]

In order to talk in a meaningful way about robustness, we need to get specific about each of these:

- property e.g., a measure of performance (throughput)
- system e.g., components? boundaries? scope?
- invariance e.g., no change? within 1%? within 5%
- perturbations e.g., component loss? changes in demand?

Ambiguity in our definitions leads to confusion.

REF: D. Alderson and J. Doyle, 2010, "Contrasting Views of Complexity and Their Implications for Network-Centric Infrastructures," IEEE Transactions on Systems, Man, and Cybernetics-Part A 40(4): 839-852.

Robustness

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Robustness to different kinds of perturbations:

Reliability	component failures
Efficiency	resource scarcity
Scalability	changes in size and complexity of the system as a whole
Modularity	structured component rearrangements
Evolvability	lineages to possibly large changes over long time scales

Fragility = the lack of invariance

REF: D. Alderson and J. Doyle, 2010, "Contrasting Views of Complexity and Their Implications for Network-Centric Infrastructures," IEEE Transactions on Systems, Man, and Cybernetics-Part A 40(4): 839-852.

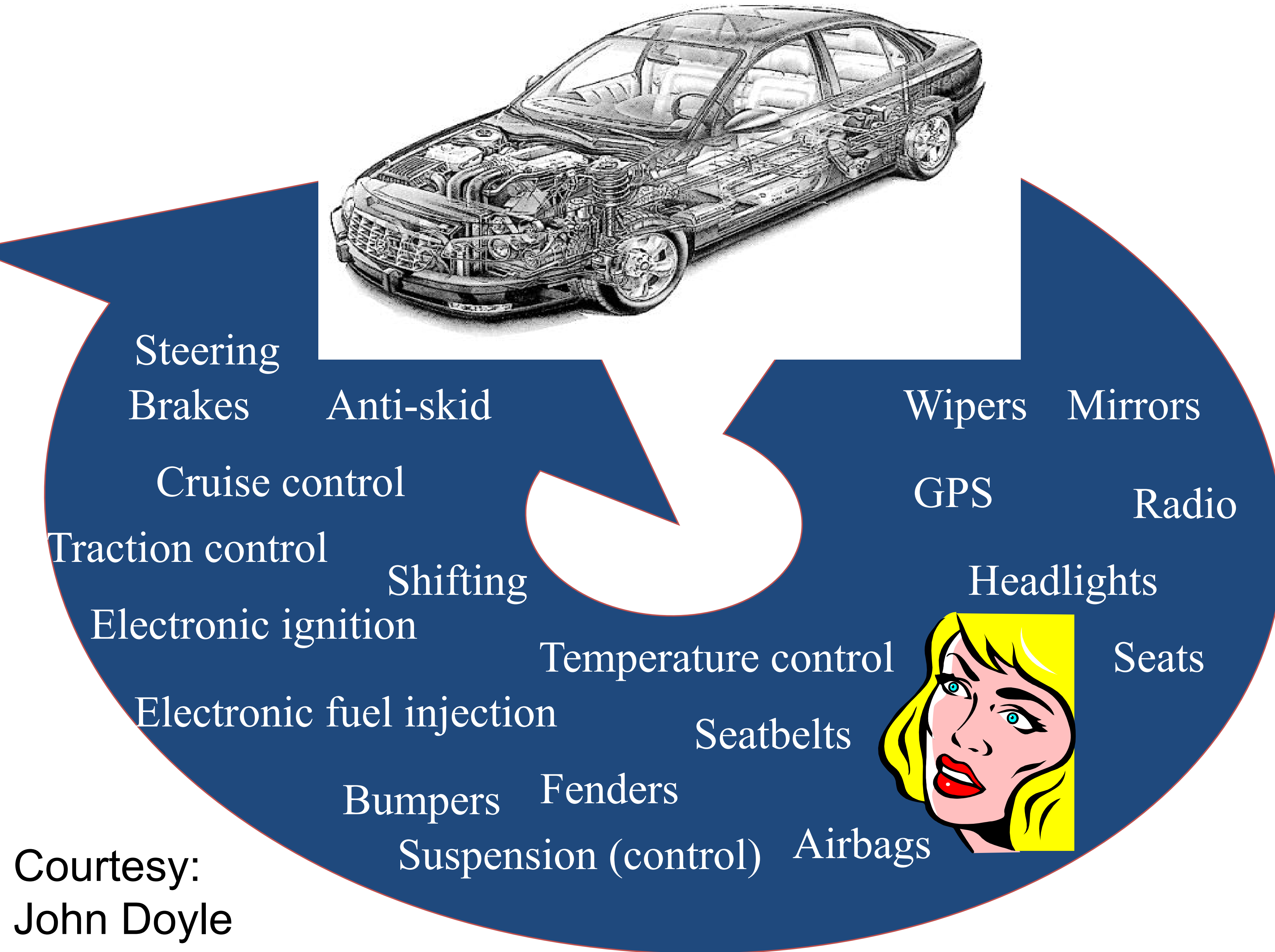
Strategies for Creating System Robustness

Increasing Complexity

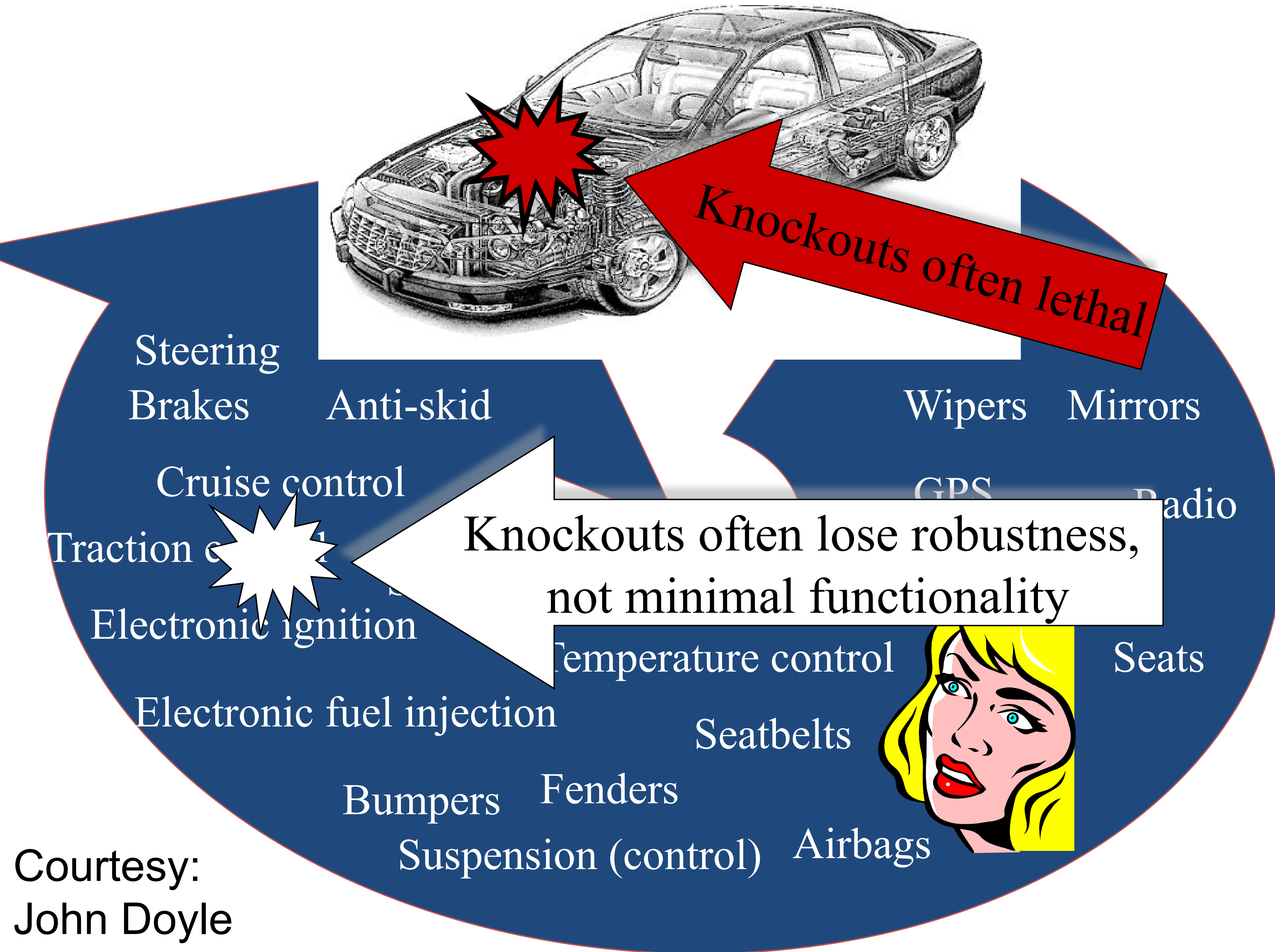
1. Improve robustness of individual components
2. Functional redundancy: components or subsystems
3. Sensors that trigger human intervention
   – Monitor system performance
   – Detect individual component wear
   – Identify external threats
4. Automated control

For many systems, much of the complexity they have is <u>not</u> the result of mechanisms for basic functionality, but from mechanisms intended to give robustness.

From "the outside looking in," it can be hard to see.



Courtesy:
John Doyle



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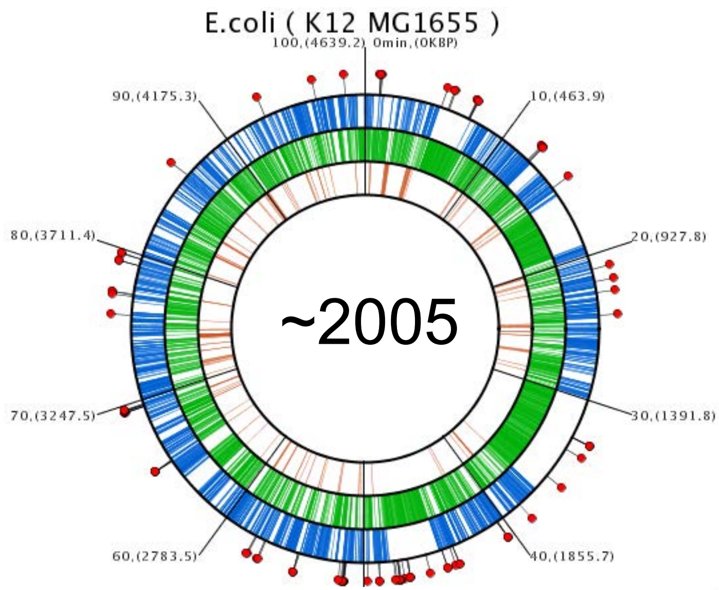
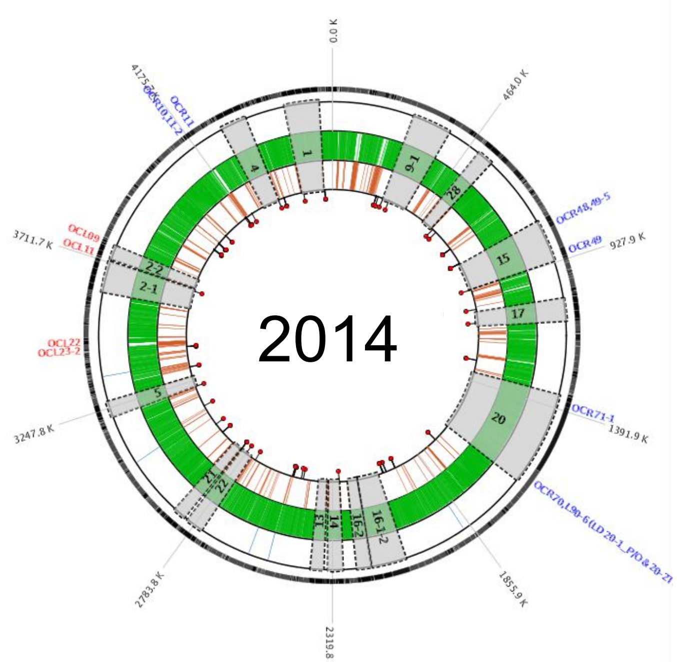
Gene networks?





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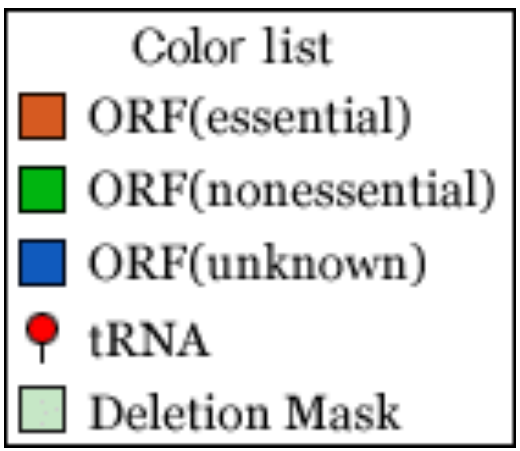
essential:	230	302
nonessential:	2373	4439
unknown:	1804	5
total:	4407	4746



Profiling of E. Coli Chromosome
http://www.shigen.nig.ac.jp/ecoli/pec

Increasing Complexity

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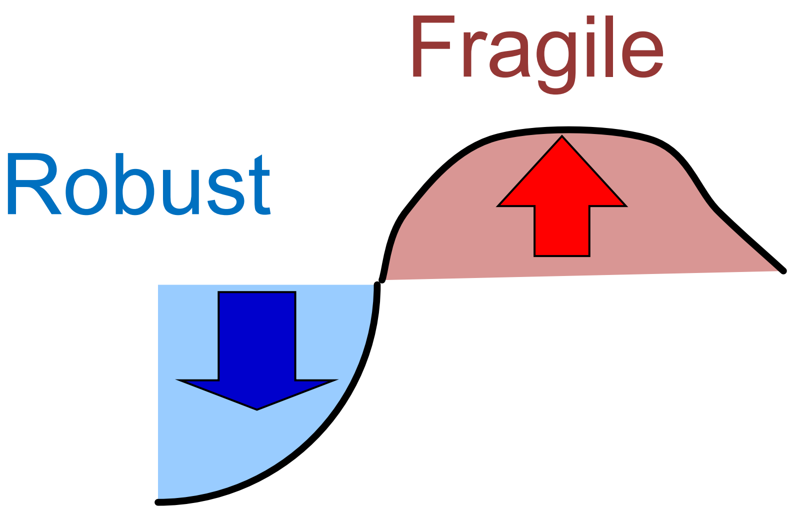
Complexity – Robustness Spiral

- The same mechanisms responsible for robustness to most perturbations
- allows possible extreme fragilities to others
- usually involving hijacking the robustness mechanism in some way

Robust Yet Fragile (RYF)

[*a system*] can have
[*a property*] ***robust*** for
[*a set of perturbations*]



Yet be ***fragile*** for
[*a different property*]
Or [*a different perturbation*]

Conjecture:
The RYF tradeoff is a ***hard limit*** that cannot be overcome.

REF: J. M. Carlson and J. C. Doyle, "Complexity and robustness," Proc. Nat. Acad. Sci. USA, vol. 99, no. Suppl. 1, pp. 2539–2545, 2002.

Human complexity

Robust

- Efficient, flexible metabolism
- Complex development
- Immune systems
- Regeneration & renewal
- Complex societies

Yet Fragile

- Obesity and diabetes
- Rich microbe ecosystem
- Inflammation, AIDS
- Cancer
- Epidemics, war

And Technologies…?

- Modern cars, planes, computers, etc have exploding internal complexity
- They are simpler to use and more robust.
- But suffer from new fragilities that are hard to understand.

Courtesy: John Doyle

Human complexity

Robust

- ☺ Efficient, flexible metabolism
- ☺ Complex development
- ☺ Immune systems
- ☺ Regeneration & renewal
- 🗐 Complex societies

Yet Fragile

- ☹ Obesity and diabetes
- ☹ Rich microbe ecosystem
- ☹ Inflammation, AIDS
- ☹ Cancer
- ☠ Epidemics, war

And Technologies…?

A few examples in the cyber domain:

- ☺ SMTP makes it easy to send email
- ☺ IP dutifully forwards packets to its best effort

- ☹ Spammers clog our inboxes
- ☹ DDOS attacks are easy to launch, hard to stop

<u>Key Message #3</u>

The Robust Yet Fragile (RYF) tradeoff means that it is not sufficient merely to add more and more technologies to "solve" the problem

Each addition has potential to create new fragilities that were not anticipated

- **Interdiction** = loss of components, loss of service
- **Hijacking** = components working in unintended ways

What about Big Data Analytics, ML, AI…?

Can't we use Big Data to prevent / manage surprise?

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VOL. 2, NO. 2, 59–67
http://dx.doi.org/10.1080/23789689.2017.1294859

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SHORT COMMUNICATION

Defining resilience analytics for interdependent cyber-physical-social networks

Kash Barker[a], James H. Lambert[b], Christopher W. Zobel[c], Andrea H. Tapia[d], Jose E. Ramirez-Marquez[e], Laura Albert[f], Charles D. Nicholson[a] and Cornelia Caragea[g]

[a]School of Industrial and Systems Engineering, University of Oklahoma, Norman, OK, USA; [b]Department of Systems and Information Engineering, University of Virginia, Charlottesville, VA, USA; [c]Department of Business Information Technology, Virginia Polytechnic Institute and State University, Blacksburg, VA, USA; [d]College of Information Sciences and Technology, Pennsylvania State University, State College, PA, USA; [e]School of Systems and Enterprises, Stevens Institute of Technology, Hoboken, NJ, USA; [f]Department of Industrial and Systems Engineering, University of Wisconsin, Madison, WI, USA; [g]Computer Science and Engineering, University of North Texas, Denton, TX, USA

ABSTRACT
Theory, methodology, and applications of risk analysis contribute to the quantification and management of resilience. For risk analysis, numerous complementary frameworks, guidelines, case studies, etc., are available in the literature. For resilience, the documented applications are sparse relative to numerous untested definitions and concepts. This essay on resilience analytics motivates the methodology, tools, and processes that will achieve resilience of real systems. The paper describes how risk analysts will lead in the modeling, quantification, and management of resilience for a variety of systems subject to future conditions, including technologies, economics, environment, health, developing regions, regulations, etc. The paper identifies key gaps where methods innovations are needed, presenting resilience of interdependent infrastructure networks as an example. Descriptive, predictive, and prescriptive analytics are differentiated. A key outcome will be the recognition, adoption, and advancement of resilience analytics by scholars and practitioners of risk analysis.

ARTICLE HISTORY
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KEYWORDS
Resilience; analytics; networks; disruptions; interdependencies

What about Big Data Analytics, ML, AI…?

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[a]School of Industrial and Systems Engineering, University of Oklahoma, Norman, OK, USA; [b]Department of Systems and Information Engineering, University of Virginia, Charlottesville, VA, USA; [c]Department of Business Information Technology, Virginia Polytechnic Institute and State University, Blacksburg, VA, USA; [d]College of Information Sciences and Technology, Pennsylvania State University, State College, PA, USA; [e]School of Systems and Enterprises, Stevens Institute of Technology, Hoboken, NJ, USA; [f]Department of Industrial and Systems Engineering, University of Wisco … rsity of North Texas, Denton, TX, USA

resilience analytics = "the systematic use of advanced data-driven methods to understand, visualize, design, and manage interdependent infrastructures to enhance their resilience and the resilience of the communities and services that rely upon them"

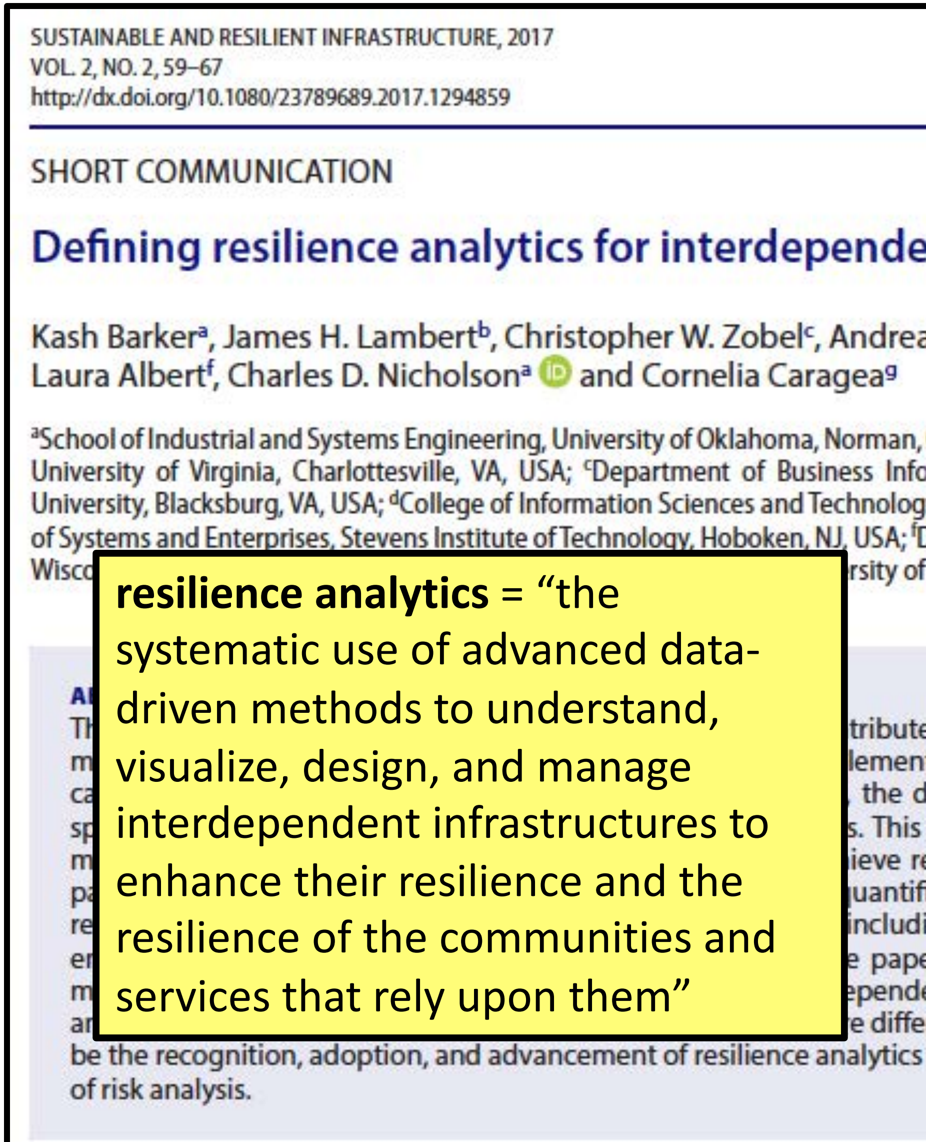
A…
Th… tribute to the quantification and
m… lementary frameworks, guidelines,
ca…, the documented applications are
sp…s. This essay on resilience analytics
m… ieve resilience of real systems. The
pa… uantification, and management of
re… including technologies, economics,
en… e paper identifies key gaps where
m… ependent infrastructure networks as
ar… e differentiated. A key outcome will
be the recognition, adoption, and advancement of resilience analytics by scholars and practitioners of risk analysis.

ARTICLE HISTORY
Received 10 April 2016
Accepted 1 September 2016

KEYWORDS
Resilience; analytics; networks; disruptions; interdependencies

What about Big Data Analytics, ML, AI…?

Can't we use Big Data to prevent / manage surprise?



SUSTAINABLE AND RESILIENT INFRASTRUCTURE, 2017
VOL. 2, NO. 2, 59–67
http://dx.doi.org/10.1080/23789689.2017.1294859

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SHORT COMMUNICATION

Defining resilience analytics for interdependent cyber-physical-social networks

Kash Barker[a], James H. Lambert[b], Christopher W. Zobel[c], Andrea H. Tapia[d], Jose E. Ramirez-Marquez[e], Laura Albert[f], Charles D. Nicholson[a] and Cornelia Caragea[g]

[a]School of Industrial and Systems Engineering, University of Oklahoma, Norman, …
University of Virginia, Charlottesville, VA, USA; [c]Department of Business Infor…
University, Blacksburg, VA, USA; [d]College of Information Sciences and Technology…
of Systems and Enterprises, Stevens Institute of Technology, Hoboken, NJ, USA; [f]…

be the recognition, adoption, and advancement of resilience analytics …
of risk analysis.

resilience analytics = "the systematic use of advanced data-driven methods to understand, visualize, design, and manage interdependent infrastructures to enhance their resilience and the resilience of the communities and services that rely upon them"

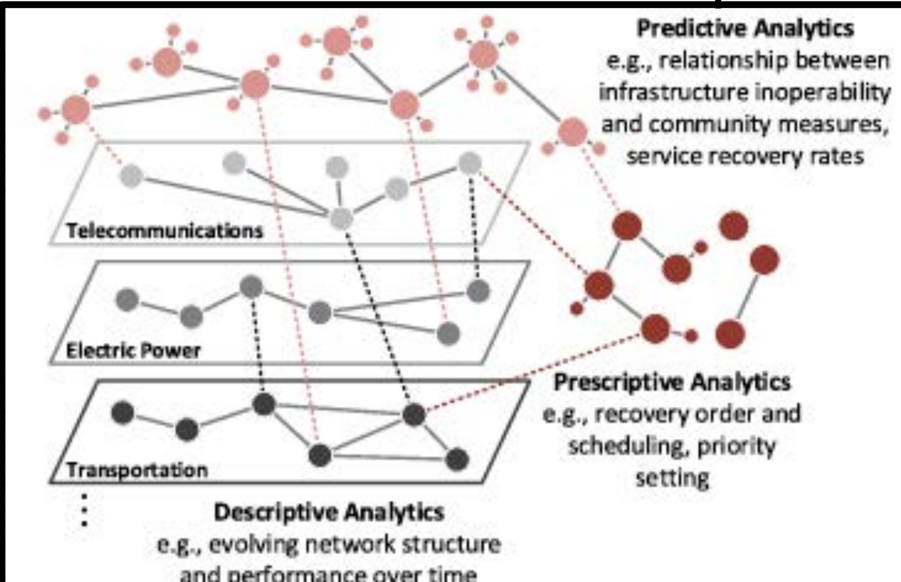

Figure 2. Descriptive, predictive, and prescriptive analytics to inform interdependent network behavior.

What about Big Data Analytics, ML, AI…?

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Laura Albert[f], Charles D. Ni…

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University of Virginia, Charlottes…
University, Blacksburg, VA, USA; [d]C…
of Systems and Enterprises, Steven…
Wisc…

Twitter Feeds +
Machine Learning Models
=
More Resilience

resilience analy…
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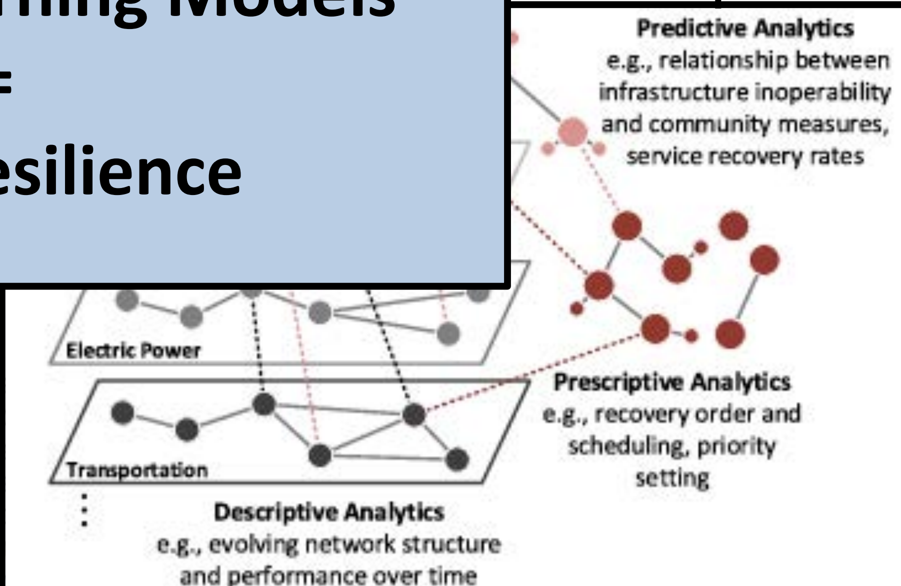

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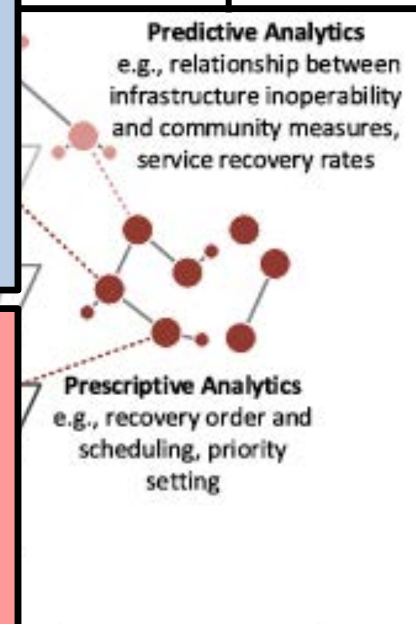
=
More Resilience

Uhh… No



…nd prescriptive analytics to inform interdependent network behavior.

be the recognition, adoption… of risk analysis.

What about Big Data Analytics, ML, AI…?

Can’t we use Big Data to prevent / manage surprise?

Risk Analysis DOI: 10.1111/risa.13328

Perspective

Rethinking Resilience Analytics

Daniel Eisenberg,[1] Thomas Seager,[2] and David L. Alderson[1,*]

The concept of “resilience analytics” has recently been proposed as a means to leverage the promise of big data to improve the resilience of interdependent critical infrastructure systems and the communities supported by them. Given recent advances in machine learning and other data-driven analytic techniques, as well as the prevalence of high-profile natural and man-made disasters, the temptation to pursue resilience analytics without question is almost overwhelming. Indeed, we find big data analytics capable to support resilience to rare, situational surprises captured in analytic models. Nonetheless, this article examines the efficacy of resilience analytics by answering a single motivating question: Can big data analytics help cyber–physical–social (CPS) systems adapt to surprise? This article explains the limitations of resilience analytics when critical infrastructure systems are challenged by fundamental surprises never conceived during model development. In these cases, adoption of resilience analytics may prove either useless for decision support or harmful by increasing dangers during unprecedented events. We demonstrate that these dangers are not limited to a single CPS context by highlighting the limits of analytic models during hurricanes, dam failures, blackouts, and stock market crashes. We conclude that resilience analytics alone are not able to adapt to the very events that motivate their use and may, ironically, make CPS systems more vulnerable. We present avenues for future research to address this deficiency, with emphasis on improvisation to adapt CPS systems to fundamental surprise.

KEY WORDS: Analytics; infrastructure; resilience; surprise

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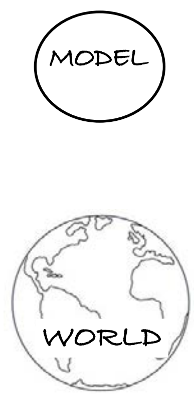
KEY WORDS: Analytics; infrastructure; resilience; surprise

<u>Key Message #4</u>

Big data analytics, ML, AI on their own are insufficient to avoid surprise.

1. How BIG DATA ANALYTICS are intended to work…



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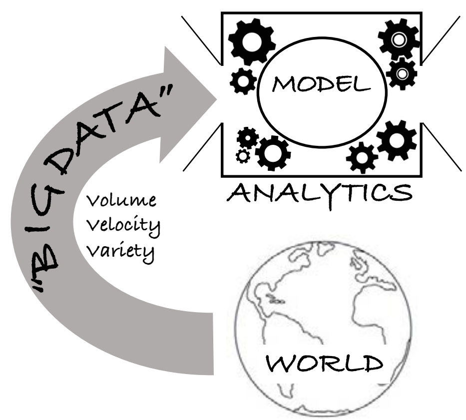

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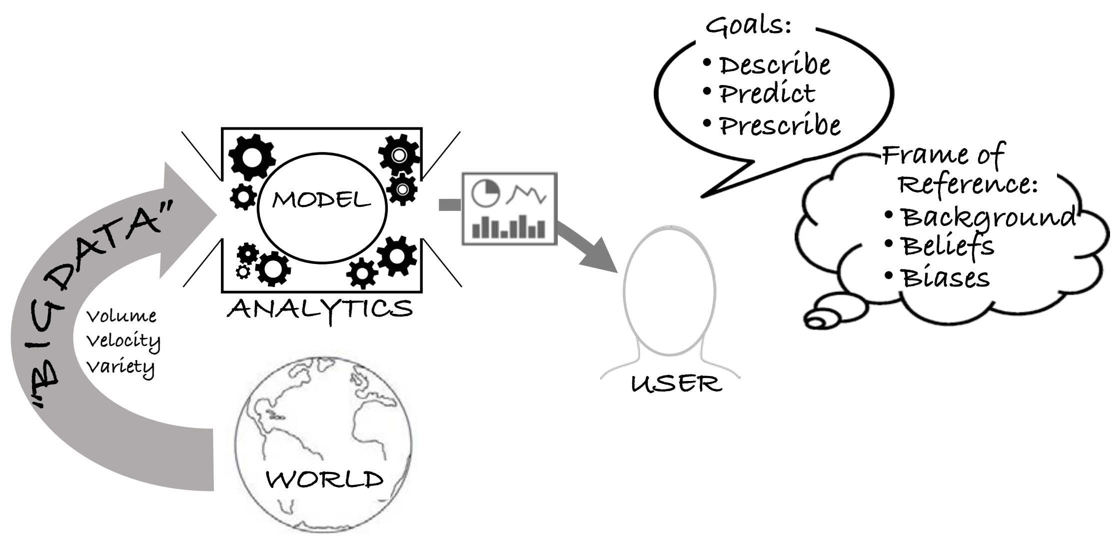

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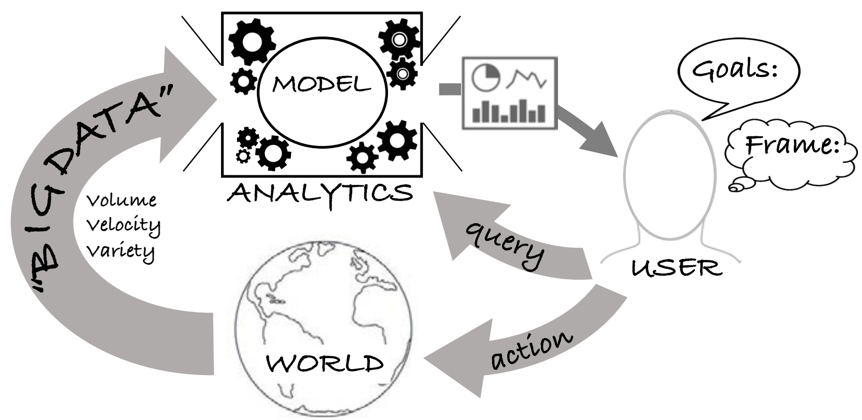
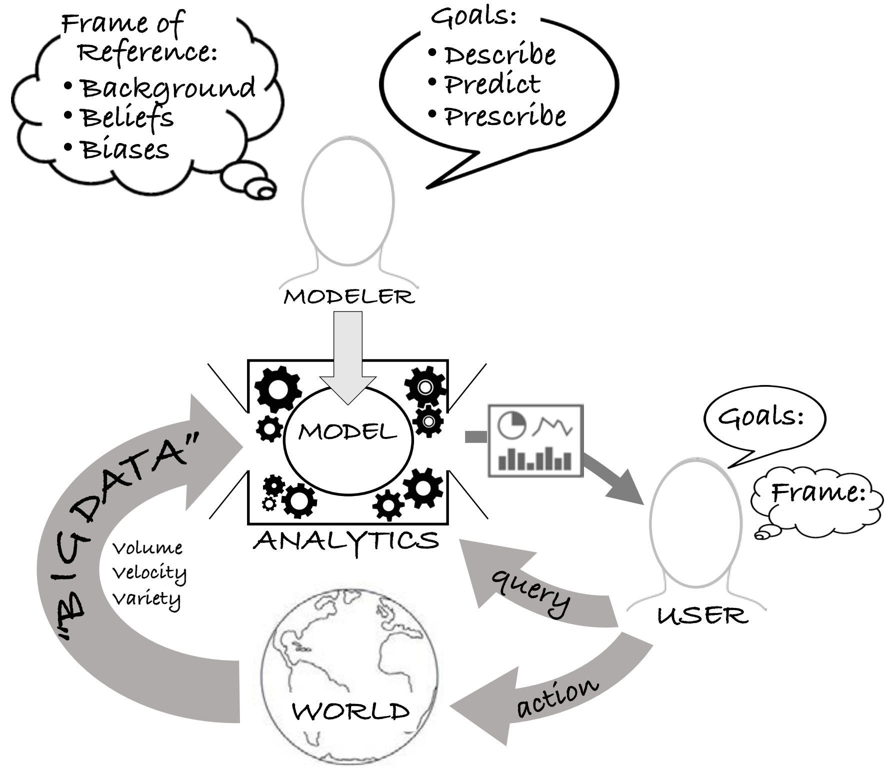


2. The role of the MODELER...



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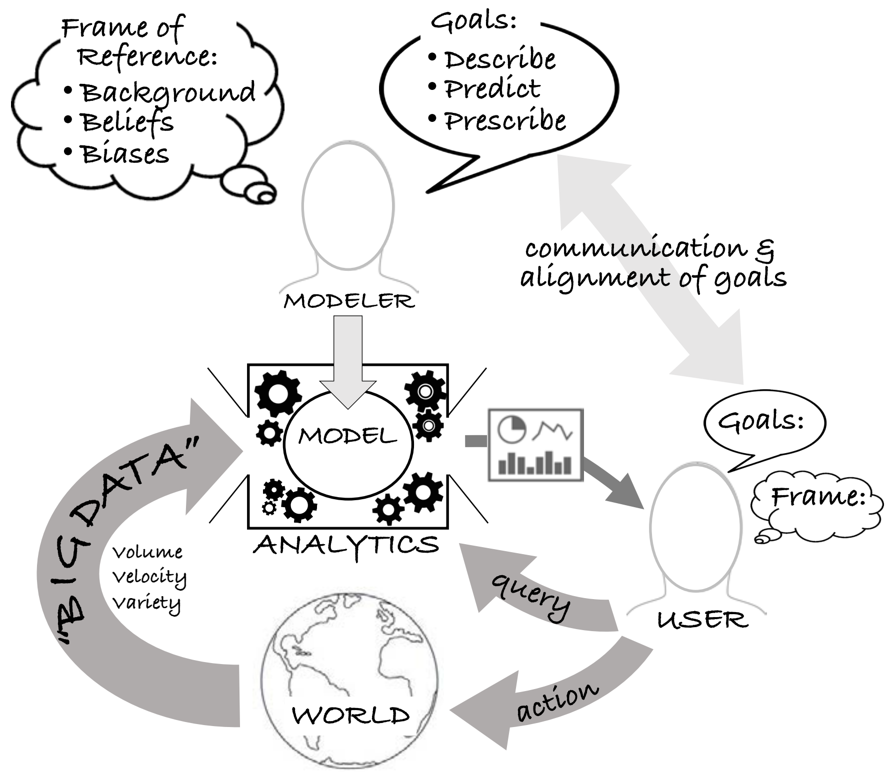

3. SURPRISE happens…

Cognitive scientists* typically distinguish between two types of surprise:

Situational Surprise

Fundamental Surprise

*References:

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Cognitive scientists* typically distinguish between two types of surprise:

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- compatible with previous beliefs
- failures and system responses are well-modeled or measurable

Fundamental Surprise

- refutes basic beliefs about 'how things work'
- one cannot define in advance the issues for which one must be alert

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- can be averted or mitigated by information about the future

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- one cannot define in advance the issues for which one must be alert
- advance information on fundamental surprise actually causes the surprise

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• failures and system responses are well-modeled or measurable	• one cannot define in advance the issues for which one must be alert
• can be averted or mitigated by information about the future	• advance information on fundamental surprise actually causes the surprise
• learning from situational surprise seems easy	• learning from fundamental surprise is difficult

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Buy a ticket and lose.

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Buy a ticket and win.

Buy a ticket and lose.

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Buy a ticket and win.

Buy a ticket and lose.

Fundamental Surprise

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Don't buy a ticket and win.

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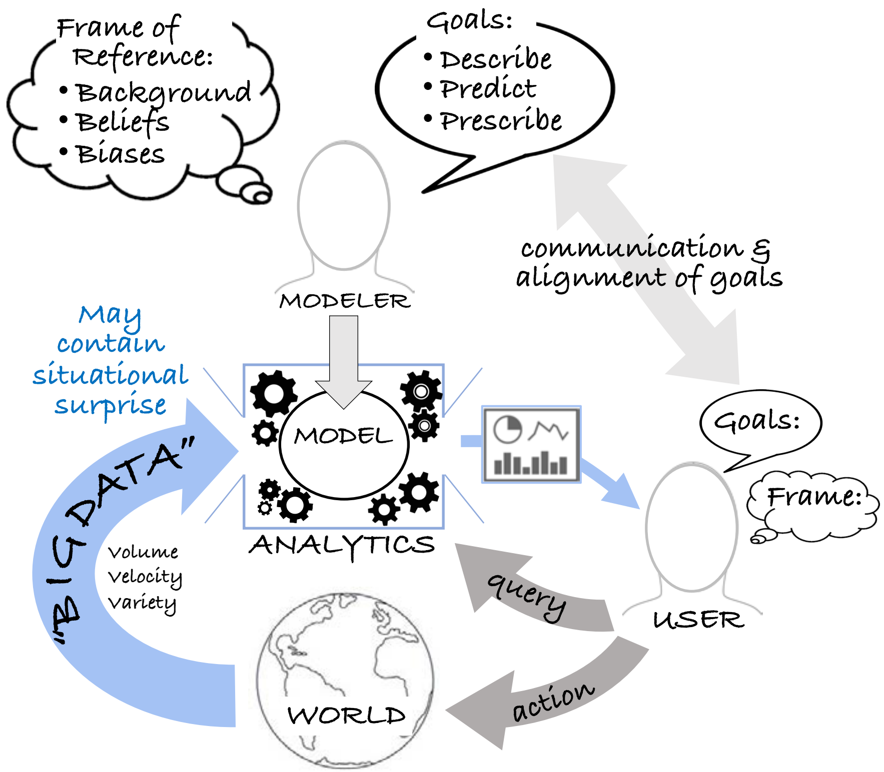
4. Situational Surprise vs. Fundamental Surprise



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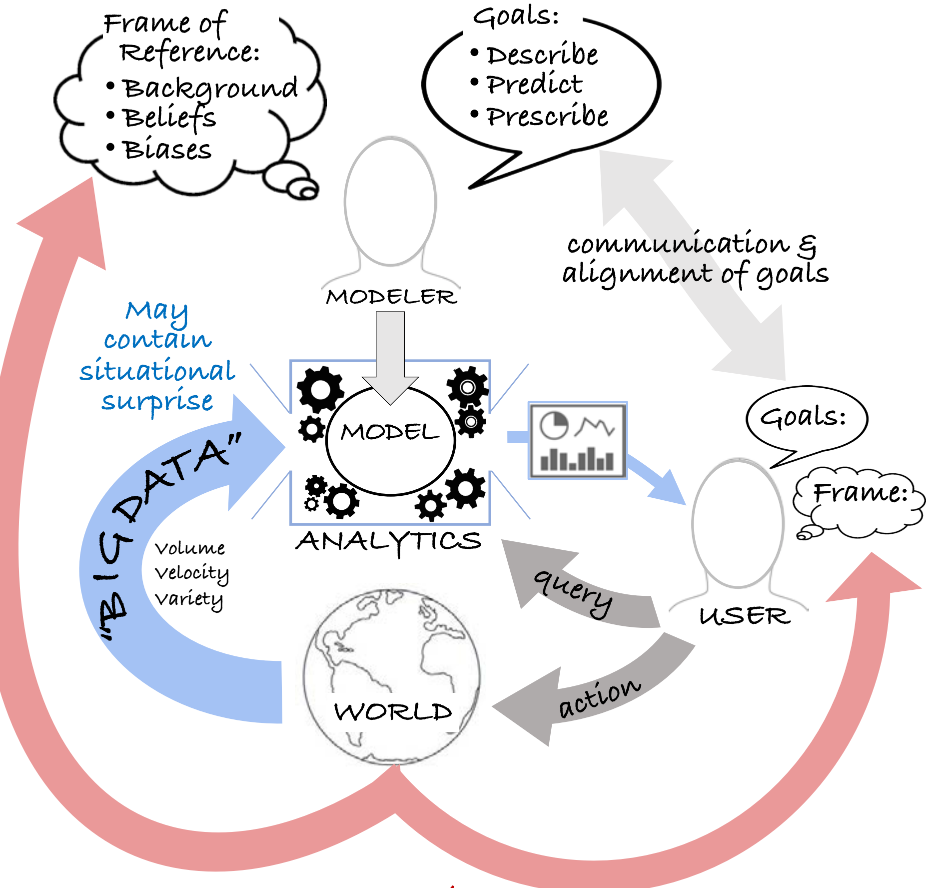
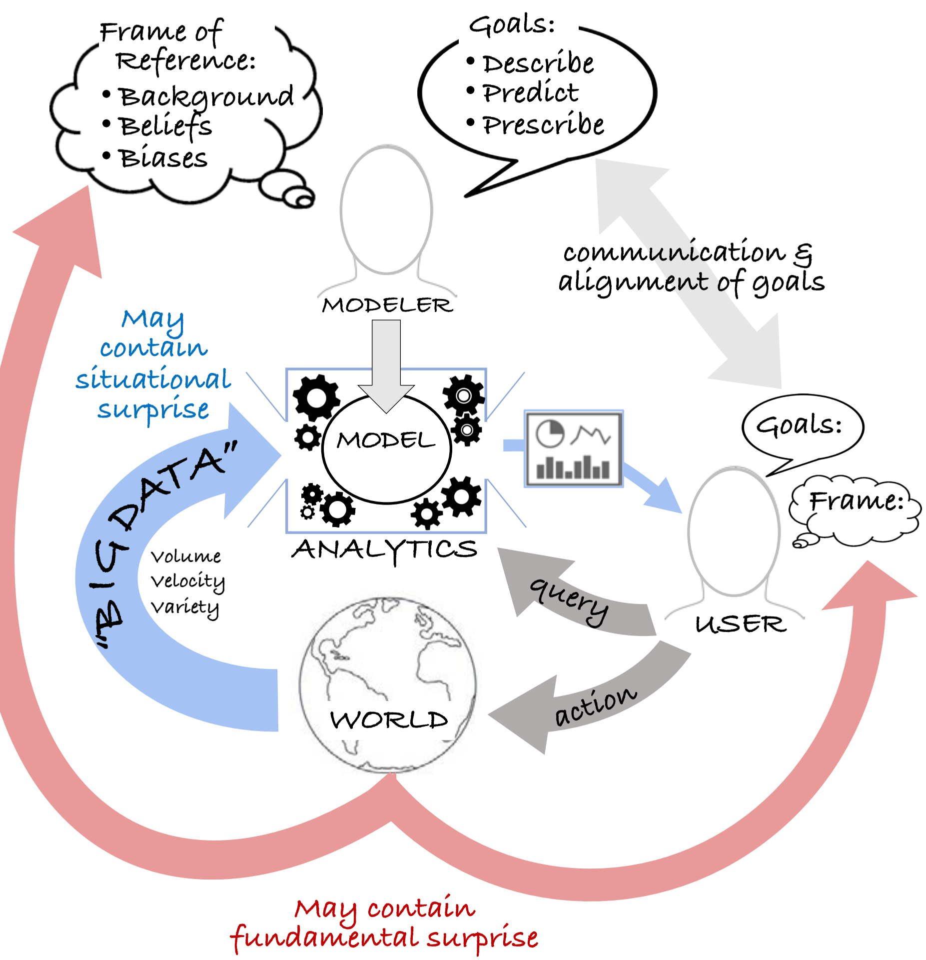


5. Responding to Fundamental Surprise (I)

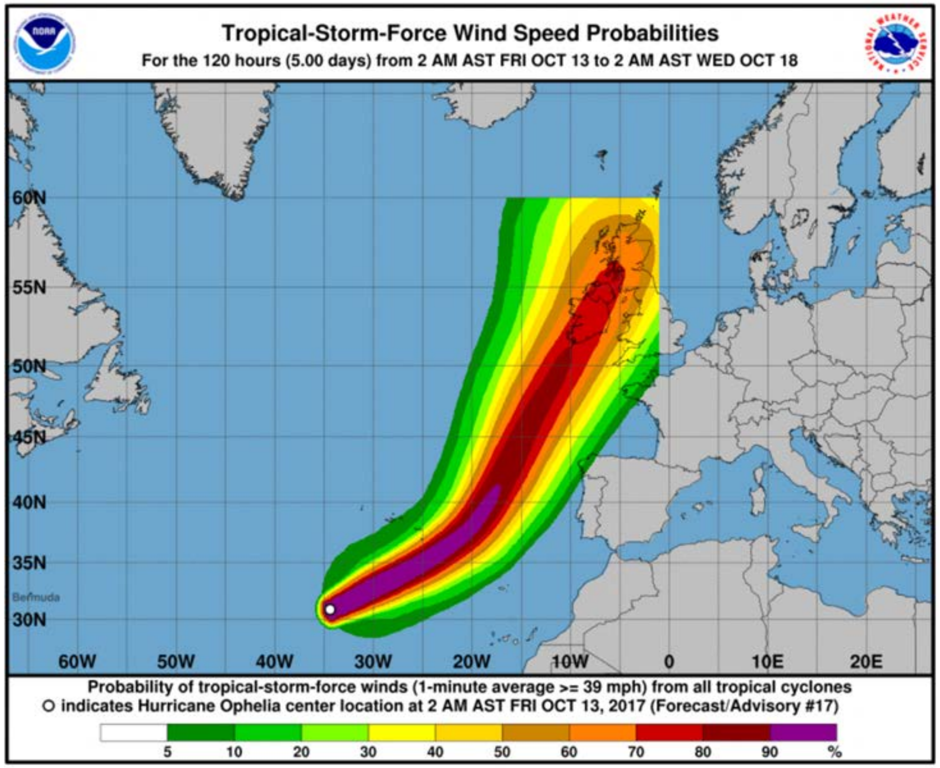
What happens when the Modeler and User are both present...?



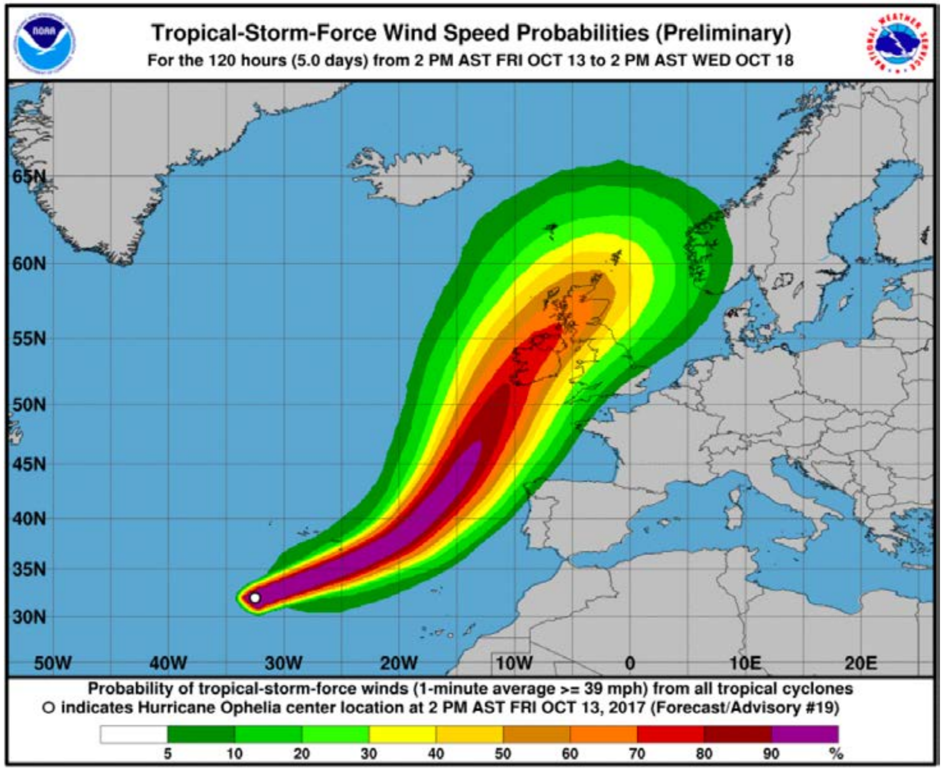
5. Responding to Fundamental Surprise (I)

What happens when the Modeler and User are both present...?

...the User and the Modeler can work together to fix the model.



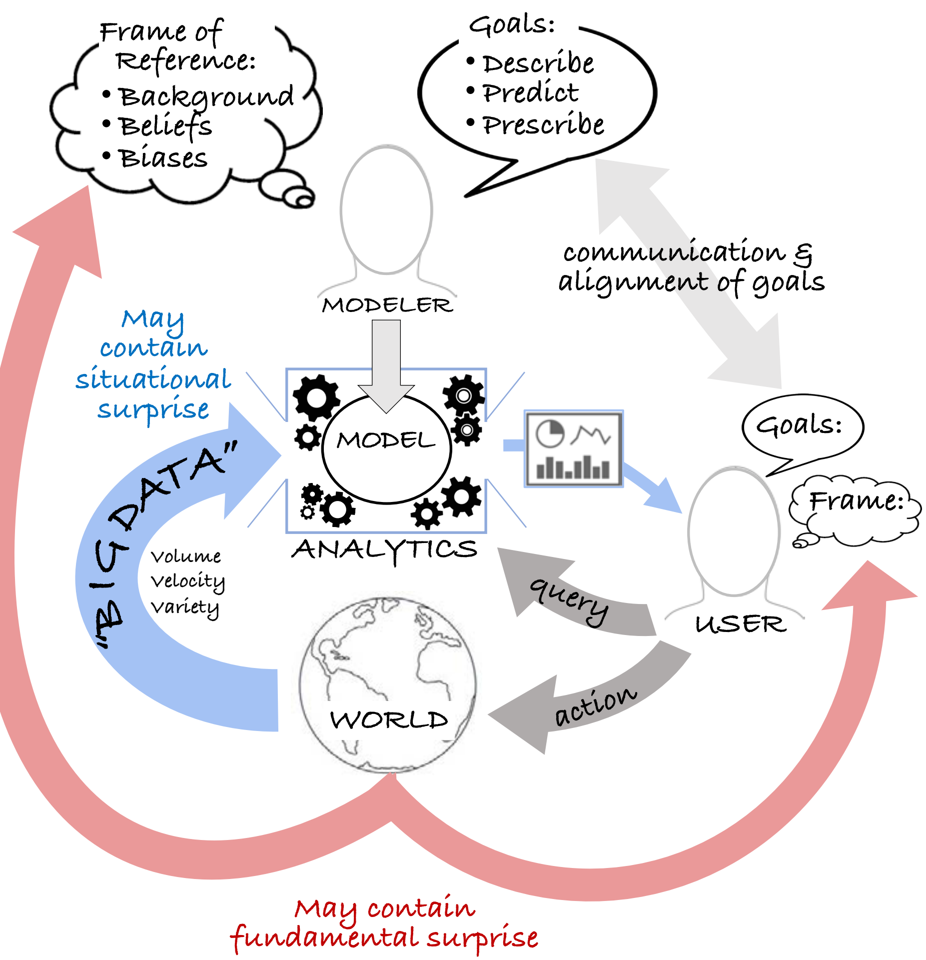
Hurricane Ophelia Oct 13, 2017 – 02:00



Hurricane Ophelia Oct 13, 2017 – 14:00

5. Responding to Fundamental Surprise (II)

What happens when the Modeler goes away…?



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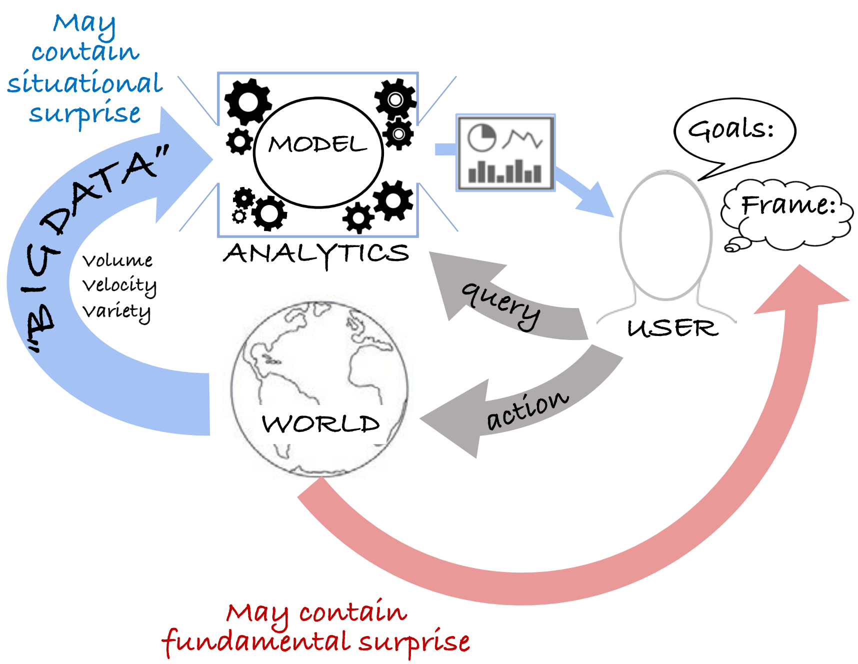

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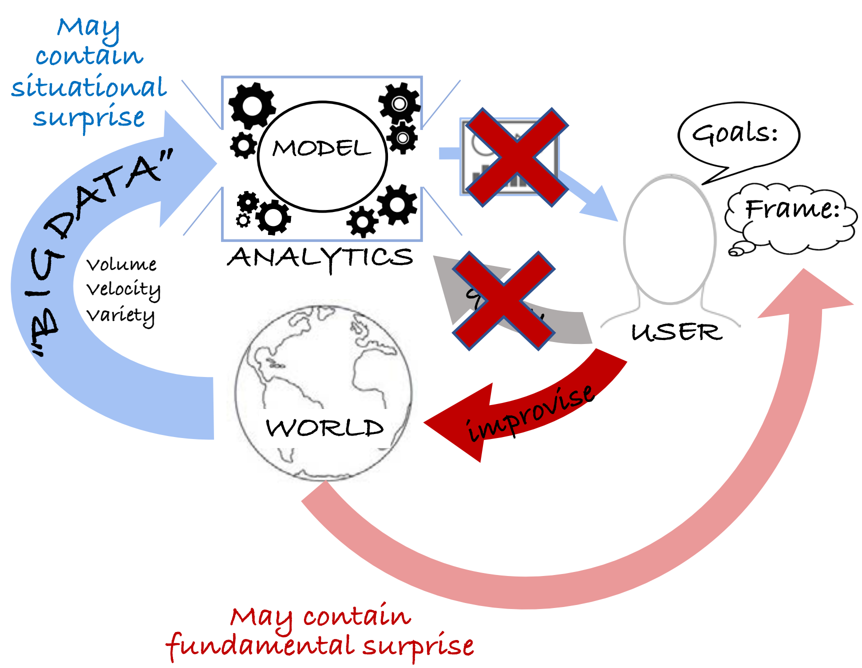
What happens when the Modeler goes away…?

…the User can only abandon the model and is forced to improvise!



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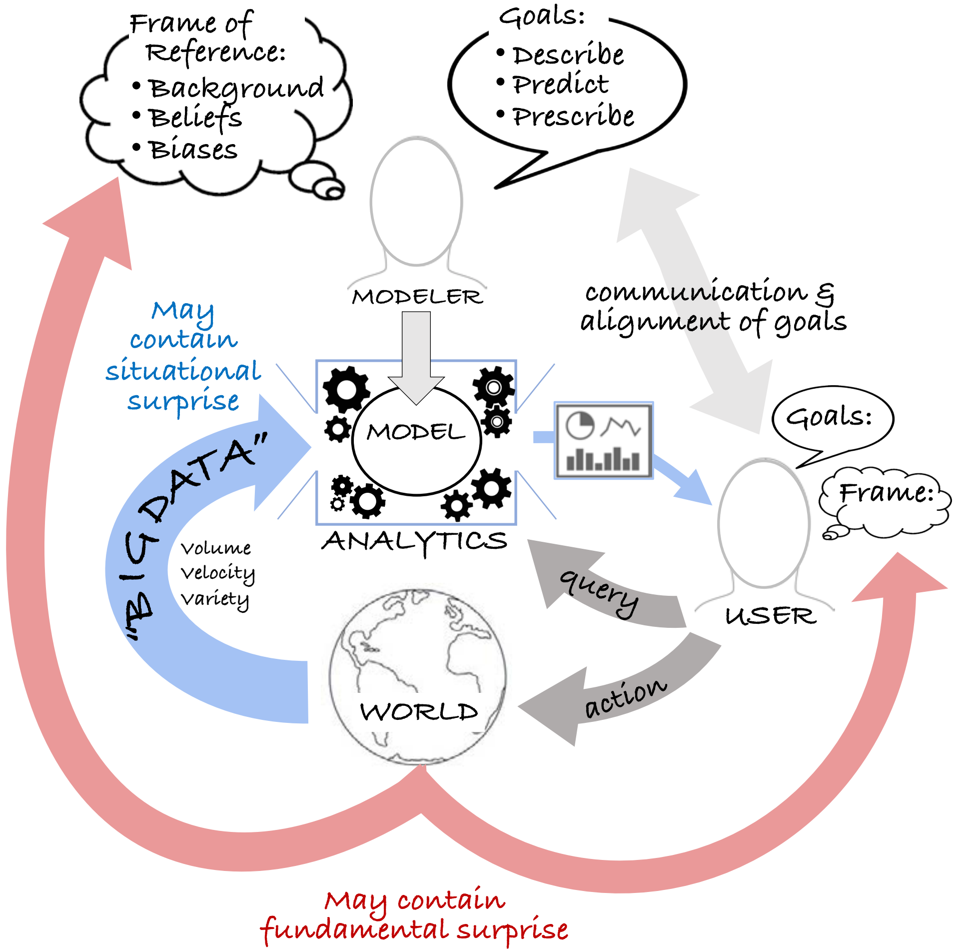
Oroville Dam, February 2017

6. Responding to Fundamental Surprise (III)

What happens when the User is automated...?



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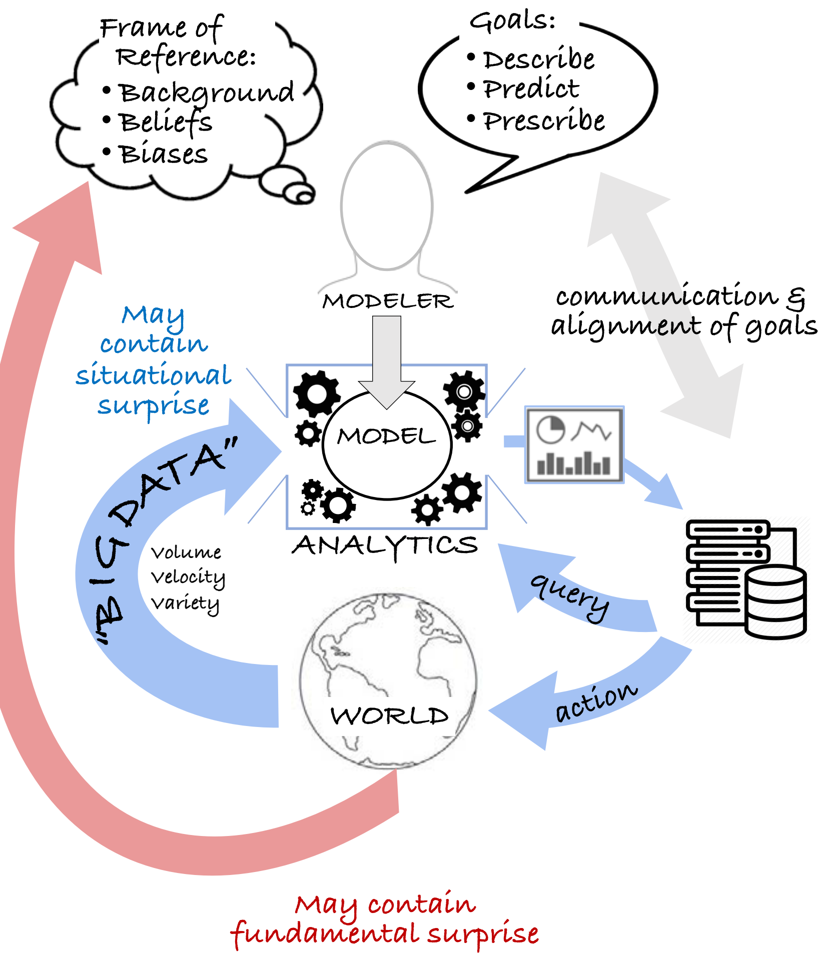

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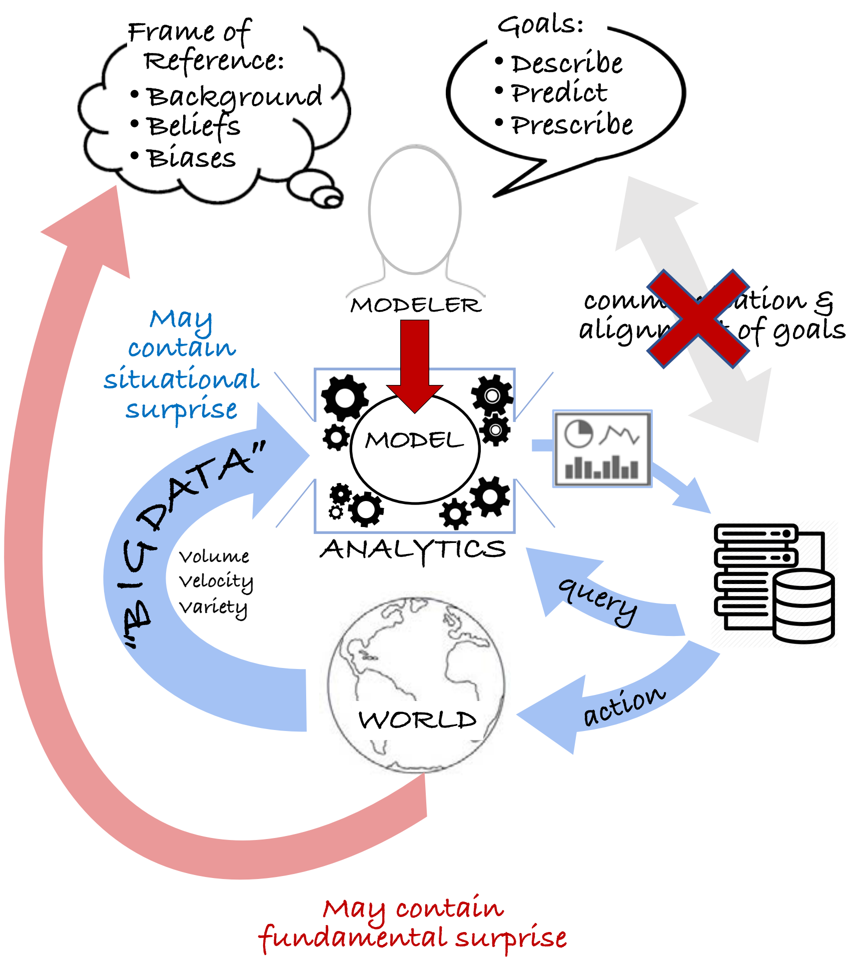


In the face of fundamental surprise, the Modeler might be too slow to adapt.

6. Responding to Fundamental Surprise (2)

What happens when the User is automated…?

…again, there are many examples of this occurring.

THE SAN DIEGO U-T UNION-TRIBUNE

FRIDAY SEPTEMBER 9, 2011 92¢ PLUS TAX

- **Massive outage:** 1.4 million SDG&E customers powerless
- **The cause:** Failure in Arizona triggered cascade of events
- **No school:** All county public schools are closed today
- **Water worries:** City issues boil-water order in some areas
- **What's next:** Power to be restored in waves into Saturday

Darkness envelops downtown San Diego as the region endures Thursday's massive power outage, which began at 3:38 p.m. SEAN M. HAFFEY • U-T

BLACKOUT

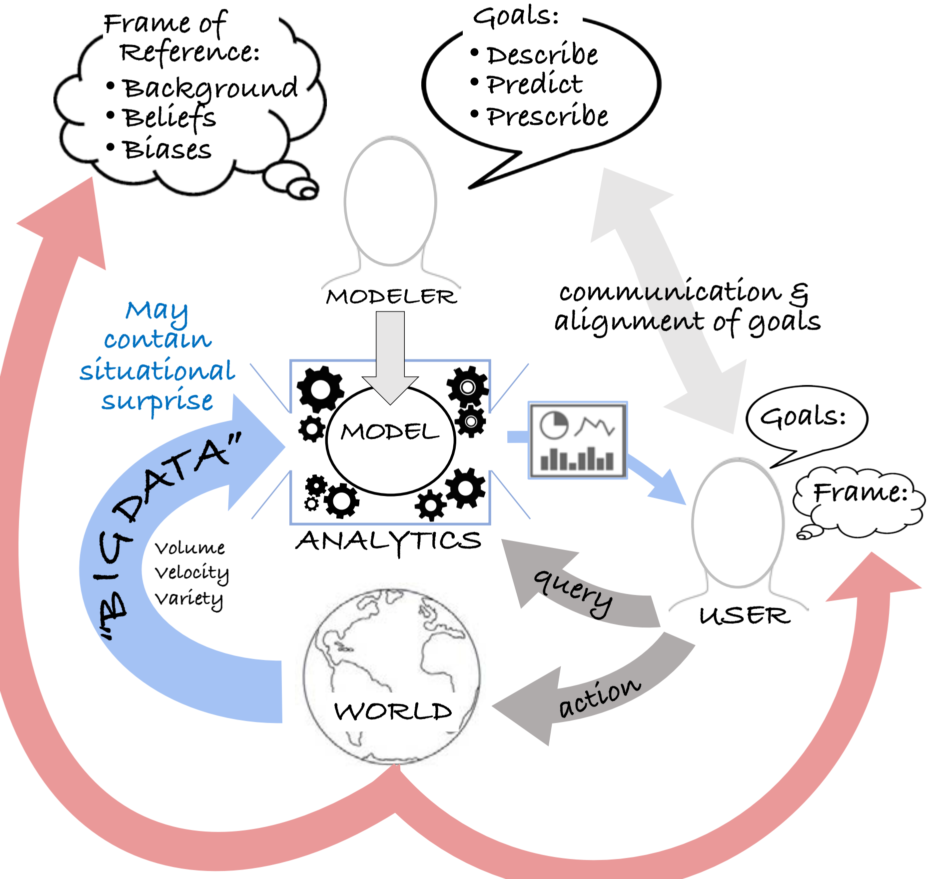
OUTAGE CALLED

2 MAIN LINKS TO

In the face of fundamental surprise, the Modeler might be too slow to adapt.

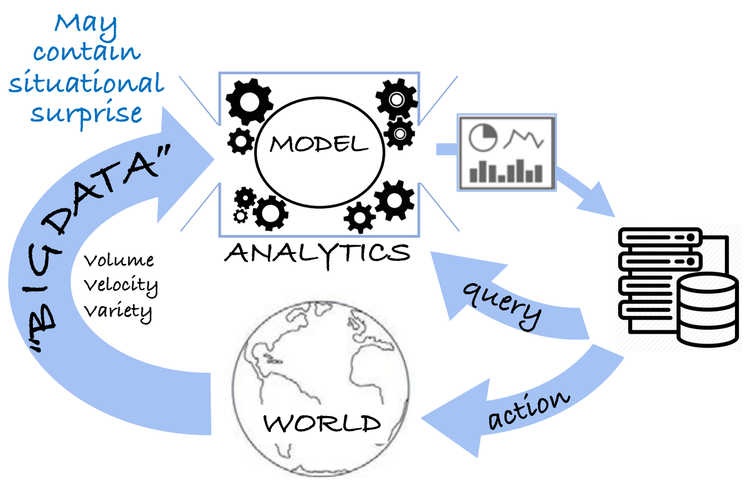
7. Responding to Fundamental Surprise (IV)

What happens when the Modeler goes away... and the User is automated...?



7. Responding to Fundamental Surprise (IV)

What happens when the Modeler goes away… and the User is automated…?



No longer any mechanism for adapting to fundamental surprise!

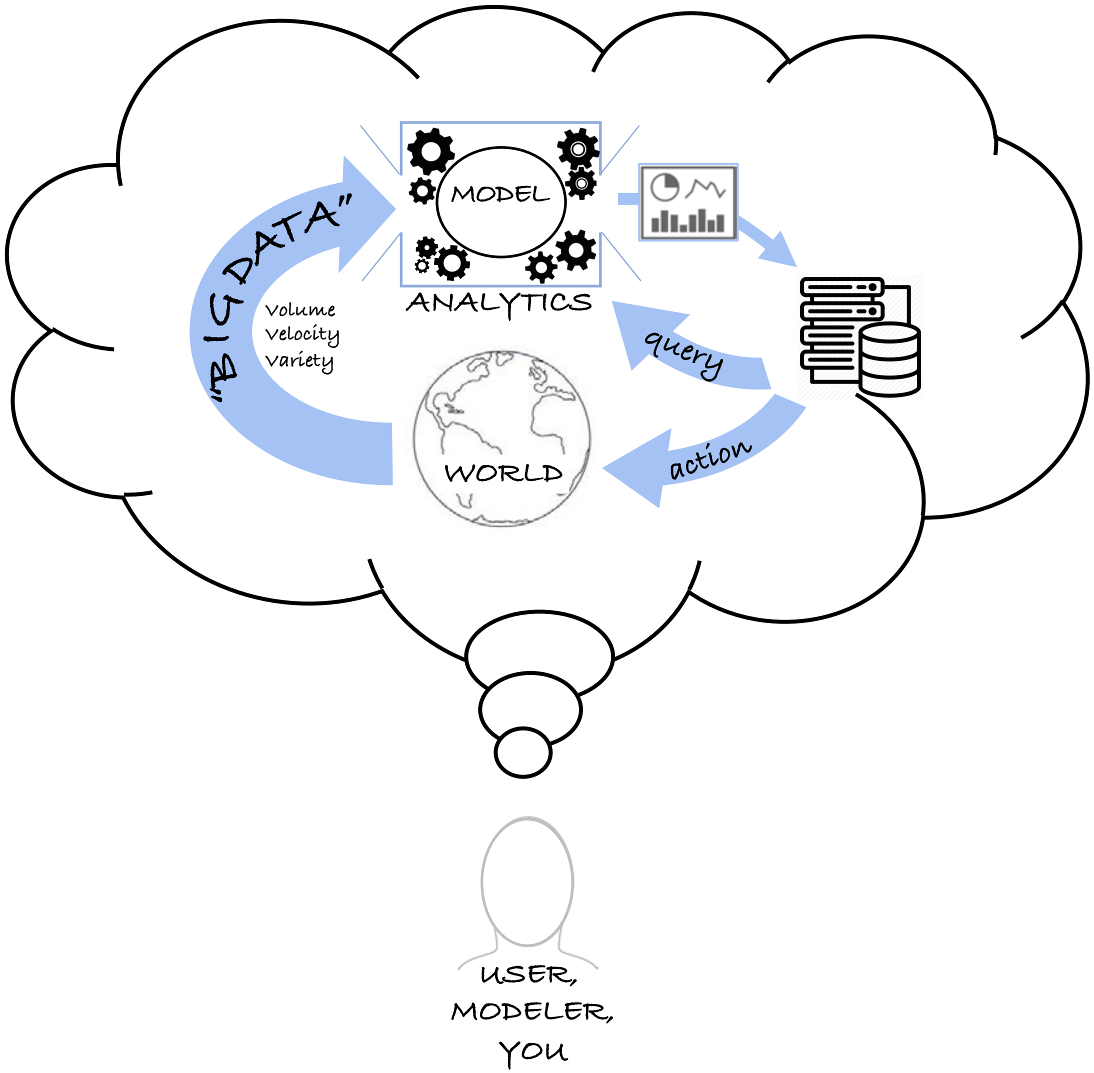
7. Responding to Fundamental Surprise (IV)

What happens when the Modeler goes away... and the User is automated...?

...we might be seeing more of these situations in the future.

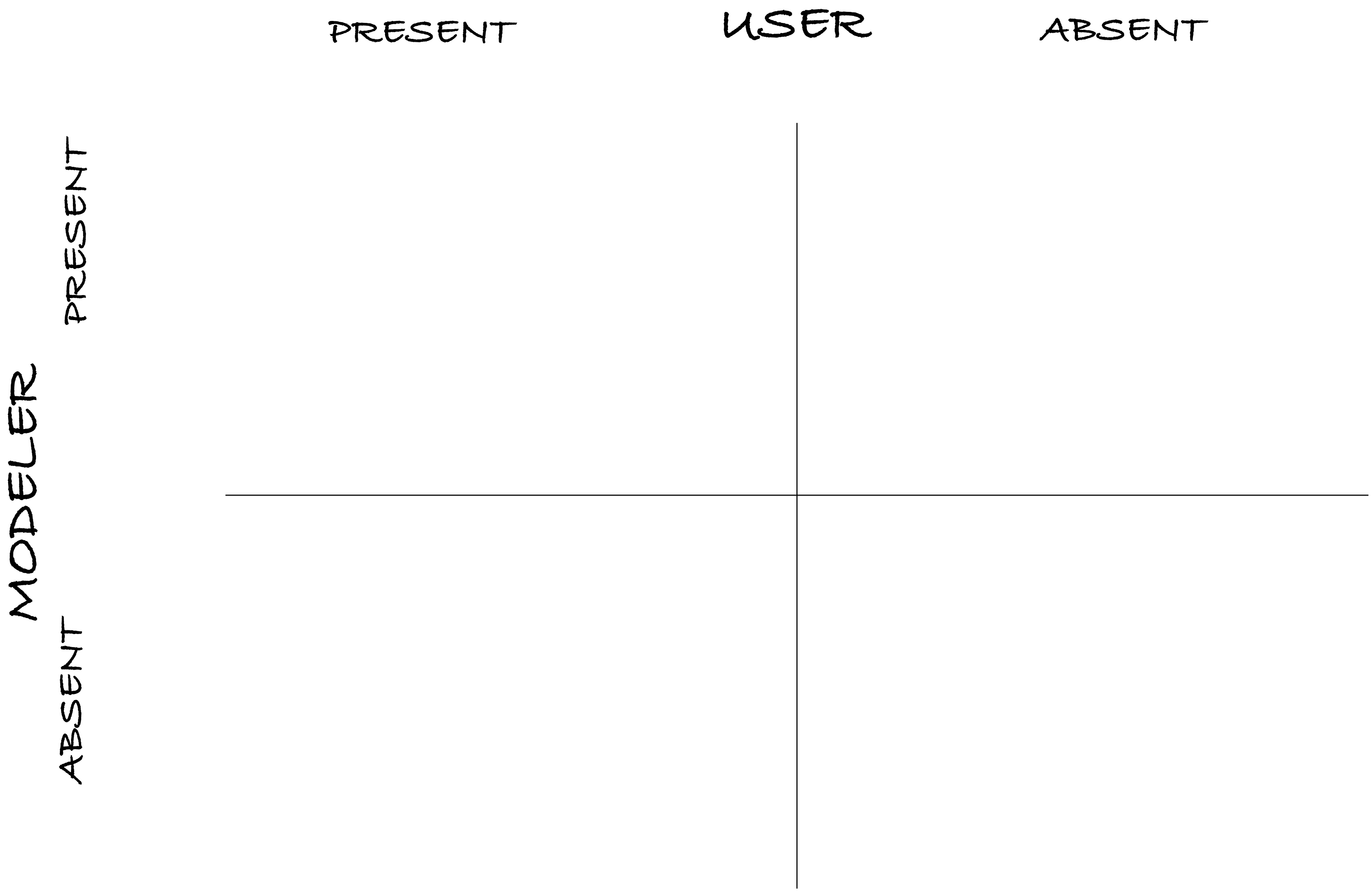
No longer any mechanism for adapting to fundamental surprise!

8. Rethinking Resilience Analytics



So we need analytics that can also adapt to fundamental surprise... but how?

8. Rethinking Resilience Analytics



8. Rethinking Resilience Analytics

PRESENT USER ABSENT

MODELER

PRESENT

- **Collective Improvisation** – unconstrained, improvised actions tacit knowledge from User / Modeler shared experiences.
- **Phronesis** – shared intent, ability to disobey User / Modeler requirements
- **Explicit Commands** – implementing User / Modeler needs based strict requirements
- **Working at Cross Purposes** – inability to share tacit or explicit requirements. Collective action worsens situations.

ABSENT

8. Rethinking Resilience Analytics

USER

MODELER	PRESENT	ABSENT
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ABSENT		

8. Rethinking Resilience Analytics

USER: PRESENT | ABSENT

MODELER: PRESENT | ABSENT

User Present / Modeler Present

- **Collective Improvisation** – unconstrained, improvised actions tacit knowledge from User / Modeler shared experiences.
- **Phronesis** – shared intent, ability to disobey User / Modeler requirements
- **Explicit Commands** – implementing User / Modeler needs based strict requirements
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User Absent / Modeler Present

- **Override the Model** – slow down, isolate, or turn off analytics before they cause damage.
- **Roll Back the Model** – revert the model to a previous version that worked.
- **Kludge the Model** – implement a "quick fix" that improves current decisions but may increase overall model deficiencies.
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User Present / Modeler Absent

- **Query the Model** – experiment with existing analytics to find new ways they can support decisions during surprise
- **Augment the Model** – find new data or observations not captured in current analytics to augment decision-making..
- **Abandon the Model and Apply Heuristics** – ignore analytics and base decisions on expert judgement gained in past or similar conditions.
- **Guess or Gamble** – make decisions without decision support based on luck.

8. Rethinking Resilience Analytics

MODELER / USER	PRESENT	ABSENT
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ABSENT	• **Query the Model** – experiment with existing analytics to find new ways they can support decisions during surprise • **Augment the Model** – find new data or observations not captured in current analytics to augment decision-making.. • **Abandon the Model and Apply Heuristics** – ignore analytics and base decisions on expert judgement gained in past or similar conditions. • **Guess or Gamble** – make decisions without decision support based on luck.	• **Fail Silent / Fail Safe** – automatic overrides shut down automated systems before they incur human or economic loss • **Safe Fail** – system failures incur losses, but in a planned and expected way • **Cascade and Catastrophe** – system failure is not arrested or absorbed in any effective way and causes even greater, compounding failures

8. Rethinking Resilience Analytics

PRESENT USER ABSENT

MODELER

PRESENT

ABSENT

Key Message #5

How will you make your system "poised to adapt" in the presence of surprise?

conditions.

- **Guess or Gamble** – make decisions without decision support based on luck.

Key Points

- Organized vs. Disorganized complexity
  - Organized complexity is more important (I argue)
- Organized systems must operate within constraints.
- Tradeoffs are fundamental.
- Everyone is trying to pick a point in the design space.
- That's not the issue. Any point will not be good forever.
- Instead: how do you move the point?
- Because… you will be surprised!
- Architecture becomes the key to sustain adaptability
- How will you design your system to be poised to adapt?

Contact Information

- Dr. David Alderson

Professor, Operations Research
Director, NPS Center for Infrastructure Defense
Naval Postgraduate School
831-656-1814, dlalders@nps.edu
http://faculty.nps.edu/dlalders

- NPS Center for Infrastructure Defense

http://www.nps.edu/cid