Data Practices

Data Practices

An empirical view of what people creating, analyzing, and managing data *actually do*. (or would do)

so that we can improve efficiency and reliability

V1. Data Practices (how do we know what works?)

V2: What's going on in the lab? (brace yourself; it ain't pretty)

V3: Data sharing (no, no, no, no, no, no. It's mine!)

V4: Data Reuse (if you didn't make it, it is hard to use it)

V2: What's going on in the lab?

Empirical extraction of vocabulary and processes

Empirical identification of bad behavior:

- metadata?? (for retrieval? use? interpretation? preservation? credit? reproducibility?)
- code documentation?
- code testing?
- workflow documentation?
- provenance availability?

and so on

Incentives to do better?

The problem (we're human, all too human)

Quasi-empirical studies

Much of the global analysis of research processes, data lifecycles, and data curation is

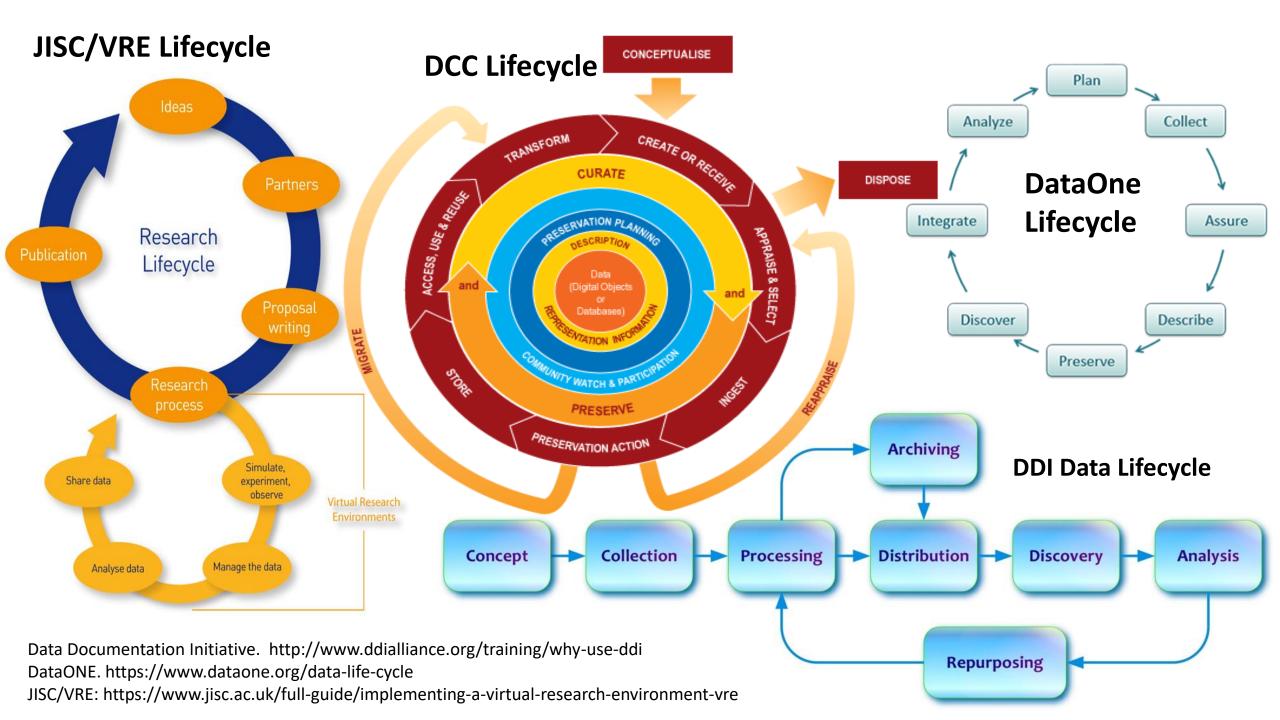
basically empirical,

but at the same time casual, not rigorous

That does mean it is wrong;

on the contrary: we don't always need a rigorous designed study

For instance:



An empirically derived typology of research data practices

Designing research

Managing data

Generating and collecting

Processing

Analyzing, interpreting, and abstracting

Representing data

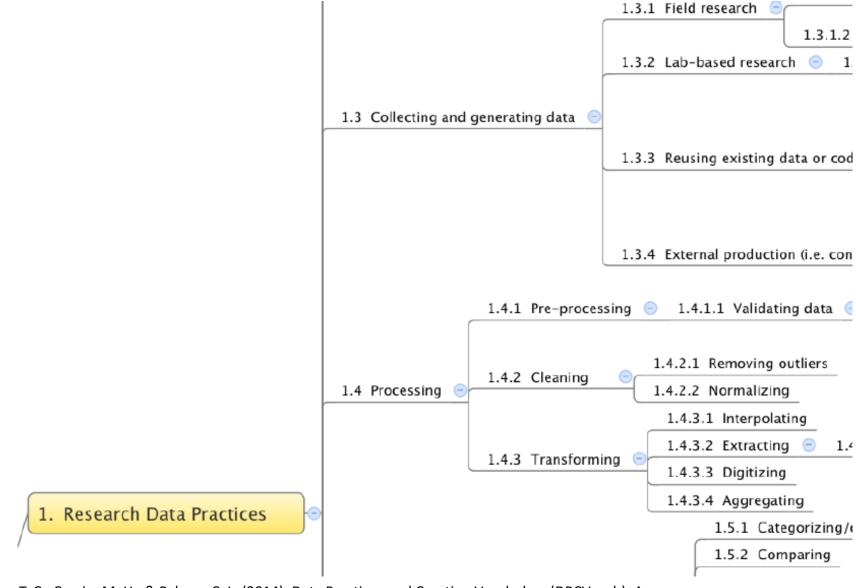
Sharing data and products

Attributing and citing data

Publishing data

Chao, T. C., Cragin, M. H., & Palmer, C. L. (2014). Data Practices and Curation Vocabulary (DPCVocab): An empirically derived framework of scientific data practices and curatorial processes. JASIST.

A fragment of an empirically derived "data practices and curation vocabulary" (DPCVocab)



Chao, T. C., Cragin, M. H., & Palmer, C. L. (2014). Data Practices and Curation Vocabulary (DPCVocab): An empirically derived framework of scientific data practices and curatorial processes. JASIST. DOI: 10.1002/asi.

Discovering (ok, confirming) bad behavior

"As a general rule, researchers do not test or document their programs rigorously, and they rarely release their code, making it almost impossible to reproduce and verify published results generated by scientific software, say computer scientists. ... scientists often lack these communication and documentation skills"

Zeya Merali "Computational science: ...Error . Why scientific programming does not compute"

Nature news feature (2010);

http://www.nature.com/news/2010/101013/full/467775a.html

...SCIENTISTS AND THEIR SOFTWARE

A survey of nearly 2,000 researchers showed how coding has become an important part of the research toolkit, but it also revealed some potential problems.

- > 45% said scientists spend more time today developing software than five years ago."
- > 38% of scientists spend at least one fifth of their time developing software.
- > Only **fill** of scientists have a good understanding of software testing.
- > Only **Example of scientists** think that formal training in developing software is important.

Metadata failures

What metadata do you currently use to describe your data, if any?

Standards	2014 Responses
DC (Dublin Core)	7.1%
DwC (Darwin Core)	2.0%
DIF (Directory Interchange Format)	1.7%
EML (Ecological Metadata Language)	9.3%
FGDC (Federal Geographic Data Committee)	8.5%
ISO 19115 (Geographic Information-Metadata)	10.2%
OGIS (Open GIS)	7.2%
Standard within my lab	16.7%
Other	8.6%

None: 47.9%

Data storage

How much of your data do you currently store in the following locations?

	Most or all of my data
External hard disk/drive storage	83.3%
On my personal computer	65.3%
Dropbox/Google/Figshare/Cloud	57.2%
On my institution's server	37.7%
On the PI's server	28.4%
On a departmental server	23.1%
On paper in my office	13.7%
In my institution's repository	11.3%
In a domain repository	9.5%
Other data repository or archive	9.3%
In a publisher repository	2.4%

Why is it so hard to be good?

We don't need a behavioral economist

to tell us that we have have a hard time giving up short-term benefits for long-term benefits, even when the long-term benefits are greater.

And that's when the benefits accrue to *ourselves* (our future selves).

How much harder it is when much of the benefit accrues to others

This is why we don't document code, test our code, add metadata to datasets, use standards, backup our files, avoid transformations at the command line, etc. etc.

Often the benefits seems indirect and elusive, and we can convince ourselves it is unnecessary

["No time to document this, but no need either: how it works is self-evident.

And no need to test it: we were careful.

And no need to back up an earlier version; this one is better, and I don't think we used that earlier version for anything important . . . (or did we?)"]

Incentives for good data practices ...?

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Scientific value

Better analysis and research outcomes
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Credit

Credit for data producers (metadata)

Data sharing = increased citations (Pinowar, 2007)

Infrastructure

Interoperable applications, systems, and data Reliability and reproducibility Efficiency Easier collaboration

Tenure and promotion assessment

Measure of being a good data steward

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