From Data Creator to Data Reuser: Distance Matters

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Abstract

Sharing research data is complex, labor-intensive, expensive, and requires infrastructure investments by multiple stakeholders. Open science policies focus on data release rather than on data reuse, yet reuse is also difficult, expensive, and may never occur. Investments in data management could be made more wisely by considering who might reuse data, how, why, for what purposes, and when. Data creators cannot anticipate all possible reuses or reusers; our goal is to identify factors that may aid stakeholders in deciding how to invest in research data, how to identify potential reuses and reusers, and how to improve data exchange processes. Drawing upon empirical studies of data sharing and reuse, we develop the theoretical construct of distance between data creator and data reuser, identifying six distance dimensions that influence the ability to transfer knowledge effectively: domain, methods, collaboration, curation, purposes, and time and temporality. These dimensions are primarily social in character, with associated technical aspects that can decrease - or increase - distances between creators and reusers. We identify the order of expected influence on data reuse and ways in which the six dimensions are interdependent. Our theoretical framing of the distance between data creators and prospective reusers leads to recommendations to four categories of stakeholders on how to make data sharing and reuse more effective: data creators, data reusers, data archivists, and funding agencies.

1 Why, when, how, and for whom should data be shared?

Recipients of research grants and authors of scholarly papers are now expected to share their data, both as a matter of public policy and of best practice. Guidelines for data sharing, such as the FAIR principles (Findable, Accessible, Interoperable, Reusable) instruct data creators in how to make their datasets available to others (Wilkinson et al., 2016). Implicit in the FAIR principles and other policy statements about data sharing are assumptions that research datasets are valuable entities worthy of stewardship, are useful to others, and that they will be reused (Borgman, 2023).

These are grand assumptions that put a heavy burden on data creators. Research projects often produce far larger volumes of data than can or should be preserved. Those data are processed and reprocessed into many states for analysis. Many instruments, many software packages, many algorithms, many protocols, and many hands may 'touch' a dataset between the origination of a project and publication of a paper. Rarely is it possible, much less feasible, to release every version of data and all associated apparatus that led to the findings. Nor is it possible to document all data and apparatus in ways that make them reusable, by all people, for all time.

Among the many tasks that may be involved in releasing data include determining the scope and type of data to release, verifying data release requirements of funding agencies and journals, cleaning data, de-identifying human subjects records, writing documentation, describing data with adequate metadata and provenance information, developing training material, registering and obtaining a Digital Object Identifier (DOI) to identify a dataset persistently, and submitting the dataset package to an appropriate archive. Most of these activities are 'soft costs' that are difficult to quantify, and that depend upon labor of highly skilled workers (Hudson Vitale, 2023; Miller, 2017; National Academies of Sciences, Engineering, and Medicine, 2020).

Recommendations to data creators for how to invest in their data are plentiful; a recent review identified 35 actions to facilitate data reuse (Koesten et al., 2020). Interview studies and

ethnographies on data reuse generally find that researchers need help in producing quality metadata, in addressing creation and usage standards, managing compliance, and more training in research data management (Donaldson & Koepke, 2022; Faniel et al., 2016; Faniel & Jacobsen, 2010, 2010; Faniel & Yakel, 2017; Mayernik, 2016, 2019; Mayernik & Liapich, 2022).

Once data are released, maintaining access to them entails further expenses that fall upon data creators, their institutions, data archives, or other parties. These costs include computational resources to host the datasets, staffing to ensure that the resources remain operational, continuing curation to migrate datasets as underlying software changes, and curatorial staff to assist in deposit, search, retrieval, and reuse of datasets.

Policy makers are increasingly concerned about the costs imposed by data sharing requirements. The U.S. National Library of Medicine commissioned the National Academies of Science to conduct a cost study of biomedical data production and stewardship. Their extensive report identified 44 cost drivers across 21 activities needed to create, maintain, and preserve biomedical data resources. While the Committee provided templates for assessing costs, including salary ranges for the kinds of labor involved, they did not attempt to establish precise costs by type of data or reuse (National Academies of Sciences, Engineering, and Medicine, 2020). In Europe, the Dutch Digital Heritage Network studied costs associated with making cultural heritage data available across their 12 member institutions, focusing on infrastructure for data archiving. Labor and staffing constituted 72% of total costs, including work to ingest, select, and add metadata (Uffen & Kinkel, 2019). Because the scope and type of investments needed to make datasets reusable by others varies widely across domains and contexts, actual costs are very difficult to determine. The few specific cost estimates and outcomes were we able to identify (see Box 1) focus on infrastructure such as data archives and on storage costs, rather than on the labor required by data creators and data reusers. Much of this labor is 'invisible work' of the sort that becomes visible only when something breaks down because the work is not done (Bates, 1999; Borgman, 2003; Crain et al., 2016).

box 1 about here

Box 1: Examples of costs and outcomes of data sharing

- The Alzheimer's Disease Neuroimaging Initiative (ADNI) provides clinical, imaging and biomarker data about the progression of Alzheimer's disease. A decade ago, when the annual project cost was roughly \$130 million, about 10-15% was spent on data sharing activities (Wilhelm et al., 2014). Per a more recent estimate, datasets hosted by ADNI have yielded more than 3500 publications from 140 million or so downloads (Veitch et al., 2022). The ADNI data also are used to improve image recognition systems.
- 2. *Our World in Data* is a popular resource for journalists and educators, with datasets on themes ranging from population statistics to sustainability, at a cost of about \$1.8 million year¹ to maintain their data, metadata, contextual articles, and infrastructure (*Our World in Data*, 2023). Recent estimates on their website indicate that their COVID-19 data is cited in 5000+ papers and CO₂ emissions data in 2500+ papers.

¹ Computed based on costs reported in the 2022 annual report of the Global Change Data Lab (parent organization of *Our World in Data*).

3. *Common Crawl*, launched in 2007, now spends roughly \$200,000 per year to maintain petabytes of openly available web crawl data (*Common Crawl*, 2023; Roberts, 2023). The use of these data to train large language models has dramatically changed the course of AI research and practice (Liu et al., 2019).

**End of box 1

Determining the efficacy of investments in data may be even more difficult than assessing costs of creation and stewardship. We turn the question of how to share data upside down, instead asking who might reuse data, how, for what purposes, and when? By taking the perspective of the prospective data reuser, it becomes possible to scope data creators' roles and responsibilities more precisely.

We develop the theoretical construct of *distance* between the data creator and the potential reuser, as originally proposed in Borgman (2015). Research data exist in a web of complex social and technical relationships, thus we develop the construct in the context of knowledge infrastructures – 'robust networks of people, artifacts, and institutions that generate, share, and maintain specific knowledge about the human and natural worlds' (Edwards, 2010, p. 17). In our formulation, the farther away a prospective reuser is from the data creator, the more labor required to reuse those data, and the less likely that successful reuse will occur. Imagine a creator who produces a dataset about energy usage in a region. For climate modelers to reuse these datasets, the best investment may be in software for ease of ingestion by models and detailed metadata descriptions of temporal capture. For teachers to reuse the same energy datasets in teaching about sustainability, the best investment may be in educational documentation. For a policy maker to reuse the dataset, the data creators' best investment may be in matching the data formats and tools to those commonly used in the science policy community.

2 Creating, Sharing, and Reusing Data

Any discussion of creating, sharing, using, or reusing research data must start by acknowledging that 'data,' even when constrained to research contexts, remains a contested concept. The term 'data' has evolved in uses and meaning over the course of scientific history, originating in mathematics before expanding into other areas of the physical and life sciences (Meyns, 2019). While 'data' are now associated with notions of evidence and facts, neither has been the case throughout history (Blair, 2010; Daston, 2017; Meyns, 2019; Rosenberg, 2013, 2018). Data are situated in contexts, are malleable, difficult to make mobile, and never are truly 'raw' (Borgman, 2015; Bowker, 2013; Latour, 1987; Loukissas, 2019; Rosenberg, 2013).

Acts of 'creating' data involve many kinds of expertise and many steps in judgment and selection. Data may originate as observations; outputs of experimental apparatus; be generated by computational models; collected as samples, specimens, or artifacts; or obtained by other methods specific to a research domain or topic of study. Many people may be involved in creating an individual dataset, each contributing expertise and making decisions about what to capture or trust. Some, but by no means all, of these decisions can be documented and associated with a dataset. As a consequence, the originators of a dataset retain the most intimate knowledge of its content (Pasquetto et al., 2019).

3 Dimensions of Distance between Data Creators and Data Reusers

Our theory development addresses questions of why, for whom, and for how long data are reusable. Given that data creators cannot anticipate all possible reuses or reusers, our aim is to identify factors that would aid data creators and other stakeholders in deciding how to invest in their data, how to share them, and how to identify potential reuses and reusers.

We identify six dimensions of distance: domain, methods, collaboration, curation, purposes, and time and temporality. These distance dimensions are social in nature; each has associated technical aspects. Technology can be used to 'lubricate' the transfer of data between creators and reusers, but also can contribute to 'friction' between data creators and prospective reusers (Edwards et al., 2011). While we attempt to characterize each distance dimension as distinctly as possible, we also acknowledge their interdependence.

Metadata, loosely defined as 'data about data,' are essential to the exchange of data products. While the term is often used as a simple shorthand for any description of information artifacts, from books to datasets, metadata has a rich intellectual history in knowledge organization (Getty Research Institute, 2008; Gilliland-Swetland, 2000; Mayernik, 2019, 2020a; Mayernik & Acker, 2018; Zimmerman, 2007). Professional practice for creating metadata varies widely across the 'memory institutions' of libraries, archives, and museums. We explore the roles that metadata play in increasing and decreasing the distance between data creators and reusers throughout the six dimensions of distance.

Data sharing and reuse involve multiple actors, with multiple relationships. These actors fall into three general groups: data creators, data reusers, and data archivists as mediators. As illustrated by examples throughout this section, data creators and reusers may interact directly or indirectly. Direct exchange occurs when creators transfer datasets to prospective reusers, such as collaborators, students, or requestors – intentionally and in real time. More commonly, reusers acquire datasets indirectly, such as via a data archive or website maintained by the data creators. Direct exchange offers the greatest opportunity for interpersonal communication about the datasets. Indirect exchange introduces more distance between creators and reusers.

3.1 Domain Distance

Studies of data sharing and reuse commonly focus on a domain of some sort, whether community, expertise, technology, language, or other grouping. The term 'domain' is frequently taken at face value, rather than explored as complex construct with subtle influences on data practices (Borgman, 2015; Koesten et al., 2020). Domain distances cascade through the other five dimensions, hence we frame it first.

3.1.1 Social aspects of domain distance

Research data are created within domains of 'human action or expertise' (Ribes et al., 2019, p. 283). Domains might be defined as broadly as art history or as narrowly as the community that employs a particular method for handling genetic material for a specific craniofacial abnormality in zebrafish. Data creators and reusers with similar expertise in theory and method will find data exchange easier than those with contrasting expertise.

The 'logic of domains' is best understood as an alternative to generic, cross-domain, or domain-independent data collections, methods, or tools (Ribes et al., 2019). Domains address common knowledge and purpose, whether for data collections, technologies, or reasoning in

artificial intelligence. Scholars in fields as diverse as philosophy, economics, education, and software engineering wrestle with the difficulties of drawing boundaries around research domains, largely due to a lack of agreement on what constitutes 'expertise.' Domain boundaries are necessary, even if drawn arbitrarily, to demarcate academic departments, funding agency programs, scholarly conferences, library collections, and data collections.

As discussed in more depth elsewhere (Pasquetto et al., 2019), differences in knowledge and expertise help to explain data reuse. A useful distinction, drawn from epistemology, is between 'knowledge that' and 'knowledge how' (Ryle, 1949). 'Knowledge that' something exists may be sufficient to locate a document or dataset of interest, but more advanced expertise in 'knowledge how' something works may be necessary to interpret and reuse those data. Degrees and types of tacit knowledge can influence the ability to interpret and reuse data (Collins et al., 2007; Collins & Evans, 2002, 2007; Galison, 1997).

Domain boundaries appear throughout the life cycle of data creation, sharing, reuse, and stewardship, whether explicitly or implicitly. 'Domain' is often framed in terms of 'community.' The Open Archival Information System (OAIS) reference model, which is widely deployed for data archives, refers to the 'designated community' – *An identified group of potential Consumers who should be able to understand a particular set of information*' – served by the data archive (Consultative Committee for Space Data Systems, 2012, pp. 1–11).

3.1.2 Technical aspects of domain distance – Infrastructure

Infrastructures for research data are typically organized by and for domains, whether by funding agencies, professional societies, or other sets of stakeholders. Domain-specific infrastructure facilitates data exchange for those who have access to the shared infrastructure, thus decreasing distance between data creators and reusers. Conversely, domain infrastructures become barriers for those without access, or whose research depends on infrastructures that are incompatible with those for which the data were created.

Astronomy, biomedicine, earth sciences, and environmental sciences are among the many domains that have invested in infrastructures to facilitate data exchange. The European Research Infrastructure Consortium (ERIC), for example, provides a legal rubric for domains large and small to develop pan-European and international data exchange mechanisms. More than 25 ERIC networks now exist for domains such as marine biology, plant sciences, clinical trials, social science data archives, language resources, and education (Directorate-General for Research and Innovation, 2023; European Commission, 2023a, 2023b). Individual countries, such as Germany (Amelung et al., 2023), France (Schöpfel et al., 2018), Netherlands (Cruz & Dunning, 2018), and the United Kingdom (Lea et al., 2016) also have established consortia to coordinate infrastructure development within and between research domains. In the United States, similar community-specific consortia are funded by agencies such as the National Institutes of Health (NIH), National Science Foundation (NSF), and National Aeronautics and Space Administration (NASA).

Astronomy offers an illustrative case study of a large, long-term, loosely coordinated, international, knowledge infrastructure funded by numerous agencies. Most major telescope observatories host data archives, alone or in partnership with a funding agency, as discussed further below under *Curation Distance*. NASA supports the Astrophysics Data System, managed by the Harvard-Smithsonian Center for Astrophysics, which hosts bibliographic records of publications in astrophysics (NASA/ADS, 2023). CDS in Strasbourg, France, manages and hosts metadata catalogs of named objects (Genova, 2013, 2018). These are but a few of the many

infrastructure components that link directly to each other, supporting intensive international data traffic. As a consequence of these and many other infrastructure investments, data exchange in astrophysics is easier than in most other domains, and is now standard practice in the field (Borgman & Wofford, 2021).

The success of domain-specific infrastructures creates barriers, and thus distance, between data creators and reusers who rely on incompatible infrastructures. New technical means are arising to bridge infrastructures, principally focused on software environments. These include virtual machines, containers and Jupyter notebooks (Boettiger, 2015; Kluyver et al., 2016). Containers and notebooks are intended to wrap data, software, and documentation into portable packages for reuse. However, these environments often presumes deep technical knowledge on the part of data reusers and may not provide sufficient information to employ the software to process a dataset (Van den Bosch et al., 2023; Wofford et al., 2020).

3.2 Methods Distance

Researchers' choices of methods are closely related to their domain and available infrastructure. Among the many methodological factors that may influence the compatibility of data creation and reuse are quantitative vs. qualitative, laboratory vs. field, human interaction vs. artifactual, size and scale, short vs. long term, analog vs. digital, hand-collected vs. machine-generated, and choices of language, whether linguistic or programming.

3.2.1 Social aspects of methods distance

Scientists and scholars learn suites of research methods as graduate students, often expanding their methodological repertoire over the course of their careers. As they collaborate with other scholars, methods may complement or converge (Darch, 2016). The ability to interpret data produced by others depends upon knowledge of the research methods by which those data were created. Researchers who are expert in experimental designs may have difficulty interpreting survey data, and vice versa. Those who work with one model organism, such as a certain type of laboratory mice, may not be familiar with methods associated with other model organisms, such as zebrafish (Pasquetto, 2018).

Choices of research methods are often a function of domain expertise and available infrastructure in the domain, university, laboratory, collaboration, or other context. Scale factors also influence methods options. To produce gigabytes or terabytes of data, whether in physics, climate science, or humanities, machine-generation is required. Data production at these large scales is necessarily standardized and typically includes automatically generated metadata. Conversely, those who conduct fieldwork, whether in ecology, ethnography, or earth sciences, may acquire small volumes of hand-crafted data that must be described and documented manually. The specific details of any of these methods may vary widely within and between research domains. Some researchers spend the careers within a narrow set of methods, while others apply methods across domains, or multiple methods within a domain.

Emergent domains of study are sources of innovation in methods, finding new ways to ask new questions. Emergent methods necessarily lack common standards and thus limit data exchange. Darch and others studied a large long-term infrastructure development in the deep subseafloor biosphere, comparing domains of science deployed (Darch et al., 2015; Darch & Borgman, 2016). Much of the shipboard technology and data handling facilities were constructed decades earlier to support physical science research. The physical scientists had standardized

their methods and data practices to facilitate data exchange within their communities. The biological scientists studied by Darch et al. were exploring new questions, using new research methods. Partly as a consequence of the lack of standardization, the biologists' data handling methods were more labor-intensive and exchange of data between collaborators was more complex. The biological scientists were engaged in a debate over when, why, and how to standardize their methods. Some argued that standardization was premature, as it would constrain the development of a new area of science. Others argued that standardizing methods would enable them to become a 'big science' sooner, grow their community, and obtain more funding.

3.2.2 Technical aspects of methods distance - Standards

The distances between data creators and reusers imposed by different choices of research methods are most readily narrowed by standardizing data production. Technical interoperability increases by layering standardized data formats, tools, software, containers, and documentation onto shared infrastructure. While standards are an embodiment of infrastructure (Star, 1999; Star & Ruhleder, 1996), they range in implementation from formal, legally enforceable standards (de jure) to informal standards (de facto) that are employed by community consensus (Lampland & Star, 2009; *National Information Standards Organization*, 2024). De facto standards are commonly employed for data exchange, methods, or protocols, whereas some fields do establish de jure standards.

The undersea biosphere case echoes earlier scientific debates about the risks of premature standardization and the benefits of standardization to advance a field (Leonelli & Ankeny, 2012). These debates continue, mostly recently in the benefits and risks of 'pre-registering' studies for the purposes of replication (Chen et al., 2018; Rocca-Serra et al., 2023; Serghiou et al., 2023). Social psychology, for example, promotes the use of registered reports, which is a mechanism to make public the protocols for collecting and analyzing data in advance of conducting research (Alipourfard et al., 2021; Nosek & Lakens, 2014).

Underlying the success of data exchange in astronomy is the Flexible Image Transport System (FITS) introduced in the late 1970s (Scroggins & Boscoe, 2020; Thomas et al., 2015). While astronomers' experimental designs may differ greatly, the ability to acquire data in FITS formats from most telescope data archives greatly simplifies the ability to exchange data and to construct interoperable tools.

Other examples of domain-specific technical standards include minimum information models in biology that prescribe basic annotations necessary to exchange microarray experimental data (Brazma et al., 2001), open image formats such as DICOM, and data repositories that meet trust standards (Swedlow et al., 2021). Chemists rely on InChI identifiers, which are text strings to identify chemical compounds uniquely (Heller et al., 2013). Infrastructure associated with InChi includes variants to improve web search and a software certification suite with corresponding logo to assert compatibility with the standard (Kim et al., 2023). Thus, potential reusers of datasets in biology, chemistry, or other fields with common data formats need to be familiar with these standards and associated tools and databases.

Scholars, librarians, and archivists began digitizing text by the 1960s, but data exchange was severely limited due to the lack of encoding standards. By the latter 1980s, the Text Encoding Initiative (TEI) formalized an XML-based standard to represent and annotate text (Ide & Véronis, 1995). By the early 1990s, the Unicode Standard was established and rapidly adopted to represent alphabets and character sets in modern languages, and later in ancient languages

(Unicode Consortium, 2024). While text produced by modern computer systems is rendered in Unicode, encoding text in TEI for purposes of textual analysis remains labor intensive (Poole & Garwood, 2020; Ruediger & MacDougall, 2023). Scholars in the humanities and social sciences who create or use textual materials in their research tend to be familiar with TEI, Unicode, and associated tools for analysis and interoperability.

3.3 Collaboration Distance

Scholars collaborate but they also compete with each other. Cooperative practices emerged in the 17th century with the first scholarly journals, when scholars and scientists saw benefits in working together (Daston, 2023). Scholars may find ways to collaborate in some areas, such as sharing data and employing common technologies, while still competing for grants, prizes, jobs, and other rewards (Borgman, 2007).

3.3.1 Social aspects of collaboration distance

In principle, collaborators should be able to exchange data easily, whereas strangers should have more difficulty in interpreting and reusing datasets. In practice, collaborations take time to mature, as researchers and teams find common ground across their domain knowledge, methodological expertise, and scholarly practices (Bowker, 2005; Jirotka et al., 2013; Olson et al., 2008; Olson & Olson, 2000; Ribes & Bowker, 2008).

'Collaboration' may refer to a formal agreement to work together, such as joint funding or organizational structure, but it can also refer to less formal collegial relationships among scholars who work together intermittently. Over the course of a career, scholars develop 'invisible colleges' (Crane, 1972) of people with whom they collaborate, exchange research papers, organize conferences, invite to speak, and may exchange data. Academic lineage is a feature of invisible colleges: advisors exchange data more readily with their current and former students, for example, than with scholars with whom they have more distant relationships. Knowledge is situated in communities, however difficult they may be to define or to draw boundaries. Social science theorizing about knowledge and communities also falls under rubrics of 'communities of practice' (Lave & Wenger, 1991) and 'epistemic cultures' (Knorr-Cetina, 1999). Individuals may belong to multiple communities concurrently, each of which evolves over time.

Collaborators retain an important advantage in data exchange over strangers, that of direct interpersonal access. Because collaborators have incentives to share data and to explain research contexts to each other, the relationship provides a means to shorten distances between data creators and data reusers.

'Data friction' occurs when transfer is impeded by differences in practices and technologies. Metadata is a common means to reduce data friction, but 'metadata friction' also can occur (Edwards et al., 2011). People use different words to mean the same things and the same words to mean different things, thus even metadata terminology can diverge across fields. Each collaborating group may draw from different metadata vocabularies or ontologies, or draw different sets of metadata from a shared ontology. Datasets often serve as 'boundary objects,' a construct used in science and technology studies to describe entities that lie at the intersection between communities (Star & Griesemer, 1989). Boundary objects such as datasets, methods, and terminology may be understood differently by each partner in a collaboration. Collaborators

necessarily translate, negotiate, and simplify meaning of such boundary objects to enable partners to work together.

3.3.2 Technical aspects of collaboration distance – Data formats

While many social factors, practices, and technologies can lubricate collaborations or cause friction (Jackson et al., 2010), data formats and associated software tools are common barriers to data exchange. Datasets created in standard formats such as FITS or TEI can be exchanged readily by collaborators with appropriate tools. Similarly, portable data formats lubricate exchange by those that enabling files to be opened with common software such as spreadsheets, popular statistical packages, and PDF readers.

Data friction arises when collaborators, or other reusers, encounter data formats for which they lack the tools to open, much less interpret, manipulate, and process a dataset (Edwards et al., 2011). All too often, datasets are output from commercial hardware or software in proprietary formats. Such files may be readable only within the same proprietary setup, including the same versions of hardware and software. If such datasets are shared with collaborators or submitted to repositories with sufficient documentation that others can recreate the environment, the datasets may be reusable or might be transferable to other environments. However, the labor and cost of setting up the technical environment to reuse a given dataset may be infeasible.

A different set of data transfer issues arises when data are encoded in formats that are human-readable but not readily machine-readable, such as PDF. Tabular data in reports or journal articles in PDF can be extracted manually, or sometimes with complex information extraction routines. Reducing format distance is a key premise of many guides to data sharing (Berners-Lee, 2009; *The Open Data Handbook*, 2023).

A common means to reduce format distance is to rely on 'lowest common denominator' formats such as CSV, Excel, or Google Sheets that can be exchanged, albeit with some loss of information. In 2020, 37% of the data indexed by Google was in tabular formats such as CSV or XLS; another 30% was in structured formats such as XML or JSON (Benjelloun et al., 2020). When collaborators with different data format and tool environments wish to exchange data, they may resort to lowest common denominator formats, despite the information loss involved. This situation occurred often in the Center for Embedded Networked Sensing, a decade-long NSF center (2002-2013). Some teams relied on Matlab for data analysis, while others employed R for statistical processing. When necessary to merge, exchange, or compare data, collaborating groups would export the relevant data to Excel spreadsheets (Borgman, Golshan, et al., 2016).

While useful for data exchange, common denominator formats often constrain the ability to structure, format, annotate, and add metadata to datasets. They also limit the functionality for subsequent data analysis. 'Self-describing' data formats arose in response; these formats have associated software libraries for data manipulation. An example is the NetCDF file format (Open Geospatial Consortium, 2024; Rew et al., 1989), widely employed in the geoscience community to exchange data about the climate. However, to view the data requires specialized software libraries that need to be wrapped either in programs written by the reuser or in user-facing applications.

Another means to reduce format distance is to bundle together multiple files (e.g., a zip file) with embedded metadata that describes file contents and relationships alternative to self-describing data formats that bundle. Bundling methods such as RO-Crate (Soiland-Reyes et al., 2022) are intended to reduce the effort required to gather information necessary to understand a

dataset. These technologies may also facilitate software portability and data sensemaking (Koesten et al., 2021).

3.4 Curation distance

Curation is the process of adding value to artifacts, whether data, documents, museum objects, or other entities worthy of stewardship. Data creators curate their data by verifying, describing, documenting, and registering datasets. Archivists, librarians, and museum curators manage artifacts to the standards and practices of their fields and institutions. The degree of curation given to any dataset varies widely, from minimal description to elaborate care and maintenance. Many (or few) hands, processes, and institutions may touch a data product over its lifetime. The type, amount, and relevance of curation a dataset receives influences the distance between data creators and reusers.

3.4.1 Social aspects of curation distance

Research data archives serve essential mediating roles within the communities they serve. Scientific archives typically serve specific types of data to support specific domains, such as gene and protein sequences in biomedicine, geospatial data in the earth sciences, or images and spectra in astronomy. Data archives vary greatly in content, in maturity, scope of community, funding sources, degree of stewardship commitment, and many other factors. A simple three-level categorization introduced by the U.S. National Science Board (NSB) in 2005 remains useful in discussing curation distance. *Research data collections* originate from research projects on narrow topics, receive minimal processing, and may be valuable for specific purposes. Those collections with longer term value and support may establish or employ community standards, becoming *resource* or *community collections*. The third category, and the one usually implied by the term 'data archive,' are *reference data collections*. The latter have long-term stewardship commitments, sustainable funding, and conform to trust and technical standards (Borgman, 2015; National Science Board, 2005).

Those research data archives with highest levels of commitment to stewardship subscribe to community standards such as the TRUST (Transparency, Responsibility, User focus, Sustainability, and Technology) principles for digital repositories (Lin et al., 2020). These principles, in turn, promote standards for digital stewardship such as the Open Archival Information System (OAIS) reference model and certification such as the CoreTrustSeal (Consultative Committee for Space Data Systems, 2012; *CoreTrustSeal*, 2024).

Some research domains make large infrastructure investments in data archives. Biomedical data archives maintained by national and international agencies are important sources of genome sequences, for example. Space-based astronomical observatories such as the Hubble Space Telescope, Chandra, JWST, and Gaia include data archives as a core component part of their scientific missions. However, support for data stewardship varies even within dataintensive domains such as astronomy. By contrast to space-based missions, ground-based astronomical observatories such as the Sloan Digital Sky Survey and the W. H. Keck Telescopes rarely receive long-term support for data stewardship in their initial mission funding. Maintenance of data resources, and access to funding for data acquisition and reuse, vary by type of astronomy mission, funding agencies, and other factors (Borgman, Darch, et al., 2016; Borgman & Wofford, 2021; Darch et al., 2020, 2021). Data stewardship also varies widely in the social sciences and humanities. Social science archives with long-term government funding for data stewardship include GESIS in Germany, DANS in the Netherlands, and the UK Data Archive. ICPSR, a US-based social sciences data archive, has served a broad international community for more than 50 years as a membership organization (Data Archiving and Networked Services, 2024; Interuniversity Consortium for Political and Social Research, 2024; Leibniz Institute for the Social Sciences, 2024; *UK Data Archive*, 2024).

Data archives can shorten the distance between data creator and data reuser through their curatorial processes, both in data handling and by direct assistance. As explored in a case study of the Digital Archiving and Networked Services of the Netherlands (DANS), archivists add value to data exchange in several ways. They work with creators who are prospective data depositors to describe, document, and validate the contents of datasets. These activities make datasets more discoverable and usable. Similarly, archivists work with prospective data reusers to aid in searching, retrieving, interpreting, and using datasets in their repository (Borgman et al., 2019). Baker and Mayernik (2020) describe in detail the workflow processes by which archivists add value to datasets contributed to repositories and how those activities differ from the work of scientific data creators. These curation activities are labor-intensive and require extensive consultation between data contributors and data creators. As a consequence, curated datasets may be released weeks or months after initially submitted to an archive.

By contrast, self-curated repositories can reduce the distance between data creators and reusers by improving the discoverability and retrievability of datasets, but to a lesser degree than domain-specific archives that invest heavily in curatorial services. Self-curated data repositories vary in the amount of automated verification applied to content, in the diversity of types of material they contain, and the degree to which they build a coherent collection for a research domain or topic. Primary advantages of repositories such as DataVerse, Zenodo, Figshare, and university digital archives are cost, speed, and scale. These repositories are akin to the NSB categories of research and resource data collections (National Science Board, 2005).

Among the many lessons learned from arXiv in 30 years of sharing preprints in physics, computing, and related fields is that 'minimalist quality control' via machine learning methods can support the 'unforgiving daily turnaround' of ingesting papers at scale. ArXiv employs mechanical means of inspection to flag problematic submissions for humans to review, avoiding some of the worst cases of inappropriate or hazardous postings (Ginsparg, 2021).

In sum, the more curation applied to datasets, and the more trusted the data archive, the less distance between the creators and prospective reusers. The greatest curation distance occurs when datasets are posted or linked with minimal documentation or validation. In a case study of the Center for Embedded Networked Sensing (CENS), some data creators posted links to datasets that immediately triggered a download of a spreadsheet or other file, with no further documentation (Mandell, 2012; Wallis et al., 2010).

3.4.2 Technical aspects of curation distance – Documentation

The greater the distance between creator and reuser, along any of the dimensions identified, the more documentation is needed to bridge the gaps. Data quality guidelines consistently emphasize the need for comprehensive documentation including rich descriptive metadata, useful human descriptions of the dataset, links to background information, and descriptions of attributes (Publications Office of the European Union, 2021).

The kinds of documentation that can shorten the distance between data creators and reusers also vary widely, depending on the form and content of datasets and array of prospective users. Metadata, as applied by professional curators, takes many forms. Among the categories of metadata identified by Mayernik (2020b) in a review of scholarly practice are these: access, administrative, archive, authentication, browse, character, descriptive, discovery, finding, identification, linking, preservation, provenance, relationships, rights, structural, technical, understanding, and use.

A study of 1,480 users of ICPSR data show that documentation quality resulted in higher levels of satisfaction (Faniel et al., 2016). In studies of data on Github, documentation is also a predictive factor for data reuse (Koesten et al., 2020). Like metadata, comprehensive documentation is expensive to create. Data creators bear sole responsibility for documentation in self-curated repositories such as Zenodo or Figshare, whereas heavily curated repositories such as ICPSR or DANS usually provide additional metadata and other forms of documentation for the datasets they acquire.

While research data discovery is improving with the development of search engines designed specifically for datasets, retrieval still relies heavily on the quality of documentation (Chapman et al., 2020). Lacking text, links, or other parameters to index, most data search engines can only assess the metadata of datasets (Gregory & Koesten, 2022). The newest, 'state-of-the-art' dataset search engines that can probe datasets first profile the datasets and then enrich the metadata with information they can extract, such as types of the columns used and dataset summaries (Castelo et al., 2021). Other advanced systems rely on the webpages associated with a dataset to allow for focused crawling and dataset discovery (Zhang et al., 2021). More broadly, dataset search engines improve with richer metadata (Brickley et al., 2019).

3.5 Distance in Purposes for Creating and Reusing Data

Research data are not disembodied natural objects that are readily repurposed. Rather, they are created in specific contexts to serve specific purposes and usually to address specific questions. The embeddedness of data in contexts is a topic well studied in philosophy, social studies of science, history, and within scientific domains. Also common to findings about the embeddedness of data are the difficulties of making data 'travel' across contexts. Considerable information loss occurs when data are removed from context (Bowker, 2005; Latour, 1987, 1993; Latour & Woolgar, 1979; Leonelli & Tempini, 2020).

3.5.1 Social aspects of distances in purposes

The usual means to facilitate data transfer between contexts is to provide information about the origins of those data, such as technical equipment, collection protocols, analysis methods for processing data, field and laboratory conditions, and other contextual details useful in interpreting them. Software used to generate or analyze data may be necessary adjuncts to datasets. Metadata schemas and ontologies also provide means to formalize data transfer.

While the problem of making data 'portable' has received considerable attention, the ability to reuse data across contexts – our concern in this paper – has received much less study. Because reuse occurs in different contexts, at different places, and at different times, and because reused datasets rarely are cited in the latter publications, matched cases are difficult to identify. Leonelli compared reuse cases in plant biology, finding that dataset reuse required considerable domain and methods knowledge (Ankeny & Leonelli, 2020; Leonelli, 2013).

In a comparative study of data reuse in biomedicine and environmental research, Pasquetto et al. (2019), found strong differences in ease of reuse between comparative and innovative purposes. Researchers frequently reused data from archives and repositories to compare or 'ground-truth' their own studies. Such reuses of available datasets were so common that neither the datasets nor the archives from which they were acquired tended to be mentioned or cited in publications. Only in rare cases did researchers seek to reuse datasets to ask innovative new research questions, thus, to reuse data for purposes other than those for which the dataset was originally collected. In these repurposing situations, the data reusers rarely found the contextual documentation sufficient. Rather, they contacted the data creators directly for more information, and usually initiated a new collaboration for the purposes of reusing and integrating their data.

Baker, Duerr, and Parsons (2016) provide a rare deep dive into how datasets, other data products, and data archives may need to be adapted to new purposes and new audiences over time. The U.S. National Snow and Ice Data Center (NSIDC) was designed originally to serve scientists within a narrow set of domains who were collecting and analyzing snow and ice data. As the value of these data became apparent for new questions about climate change, and for a much broader array of scientists and scholars, the NSIDC invested in new ontologies and metadata, and extensive recataloging of older data to serve new purposes. These were expensive investments by the NSIDC and its parent funding agencies, justifiable by the importance of the scientific questions to be addressed.

Other cases exist in citizen science, such as the Zooniverse (2024) project on 'old weather,' in which participants transcribe hand-written weather descriptions from sources such as 19th century ships' logs. Personal diaries from earlier centuries that record dates when flowers bud or bloom, when birds arrive, and other observations of the natural world also are proving useful in assessing climate change. Repurposing old records is useful in certain circumstances, but does not scale. In most cases, those who wish to reuse for new purposes must rely on available documentation and on access to the data creators, where possible. As discussed above under *Curation Distance*, the missions of data archives are framed in terms of serving their 'designated community,' with an acknowledgement that the community may change over time.

3.5.2 Technical aspects of distances in purposes - Interfaces

Data reusers frequently encounter difficulties in identifying, retrieving, and interpreting datasets created for other purposes. Among the few technical means to bridge these gaps are software interfaces that enable two or more programs to work together. Most are known as Application Programming Interfaces (API). These interfaces can reside on a familiar platform, such as MacOS, Windows, Linux, Apple iOS, or Android, to provide dataset views and analytical tools for data in repositories. APIs thus may expose parts of a dataset, both guiding and constraining data exploration. While not a substitute for quality dataset documentation, APIs may be especially useful for those performing cross-disciplinary research (Jia et al., 2022).

APIs also are useful for curated reference collections that serve broad communities and whose data resources may be of interest to larger audiences. For example, ProteomicsDB, a provider of mass spectrometry-based proteomics data, provides multiple interfaces to explore, render, and identify proteins and their expression in organisms. They offer a comprehensive API that allows connections with other data providers and tools to perform predictive analytics (Lautenbacher et al., 2022). ProteomicsDB deployed new interfaces as means of meeting the FAIR principles (Wilkinson et al., 2016).

In astronomy, the World Wide Telescope, which provides an interactive user interface to explore images from multiple telescopes, has led to usage from introductory college courses to planetariums as well as by astronomers for their own scholarly communication (Rosenfield et al., 2018; *WorldWide Telescope*, 2024).

3.6 Distances in Time and Temporality

Whereas the distinction between time and temporality is a basic principle of classical philosophy (Drucker, 2009), these topics rarely are addressed explicitly in data creation, sharing, and reuse. Time and timelines are usually linear and unidirectional, whereas temporality is relational. Events can occur before, after, during, or concurrent with other events, and may be discontinuous or iterative. Data processing involves many time-related factors that may influence the social and technical distances between creators and reusers.

3.6.1 Social aspects of distances in time and temporality

Temporal factors pervade data creation and reuse, both implicitly and explicitly. The most obvious distance aspect is elapsed time between creation of a dataset and time when a prospective reuser wishes to employ those data in later research. If the elapsed time between origin and reuse is relatively short, the parties may readily exchange knowledge about the dataset. If the elapsed time is relatively long, reusers must rely on available documentation and context. Months, years, or centuries may pass between data creation and reuse. Practices and circumstances evolve. In the case of digital data, hardware and software ecosystems degrade. Some datasets become more valuable over time, while others rapidly decay in value.

To reuse a dataset, a researcher usually needs to know how, why, where, and when it was collected. 'When' can be as simple as a time stamp, but even a time stamp is relative to local clocks, or may be a sequence in a workflow. Scholars in all fields, from artificial intelligence to ancient history, encounter temporal factors that influence how data are collected and interpreted. Drucker (2009) develops 'temporal modeling' in the context of the humanities, albeit with a broad framing that is relevant to many areas of scholarship. Representations of time must accommodate 'retrospective, simultaneous, and crosscut temporalities' (Drucker, 2009, p. 37). Allen and Ferguson (1997) address ways to represent actions and events in 'interval temporal logic,' building upon Allen's canonical work on the many ways to represent time (Allen, 1991). Their models also explore the complexities of discontinuous, overlapping, and nonlinear nature of time, with the goal of representation for computing purposes.

Concerns for time and temporality in the reuse of data are most often framed in terms of data 'life cycles.' The trio of short perspective articles that frame the scope of data science in the first issue of this journal illustrate contrasting perspectives even on this notion. Wing (2019), a computer scientist, took a linear view of data life cycles, emphasizing the privacy and ethical concerns at each stage. Leonelli (2019), a philosopher of science, explored a data-centric view of science, the ways in which data may be potential or actual evidence, and relationships between objects, data, models, knowledge, and interactions with the world. Borgman (2019), an information scientist, explored how data creation and stewardship vary by type of data and community, and over time, considering the 'lives and after lives' of data. The relational and infrastructural views of data we take in this article raise questions of data governance, thus, who decides how data should be managed over the long term, and by what criteria – a concern that extends well beyond research data (Davidson et al., 2023; O'Hara et al., 2021).

Leonelli and collaborators, in their work on 'data journeys,' are among the most explicit in studying temporal relationships in the creation and reuse of data. In their simplest formulation, the distance between data creator and reuser increases with time. When someone attempts to reuse data shortly after those resources become available, the reuser is most likely to have access to similar expertise and infrastructure. The greater the time elapsed between creation and reuse, the less likely that the data creation environment can be replicated and the more that the circumstances of data creation have changed (Leonelli, 2013; Leonelli & Tempini, 2020).

3.6.2 Technical aspects of Distances in Time and temporality – Data provenance

In the context of data management, provenance is the category of metadata used to document relationships over time (Lynch, 2001; Mayernik, 2020a; Pasquier et al., 2017). Provenance is a more elusive term than it may appear. The ability to trace relationships over time, such as origins, custody, amendments, ownership, transformations, or workflows, is essential to establishing chains of evidence and trust (Bettivia et al., 2022; Mayernik, 2019).

Provenance metadata are computable representations of how a document or dataset came to be. Data provenance mechanisms such as the World Wide Web Consortium (W3C) recommendation on provenance, PROV (Moreau & Groth, 2013), use relative orderings of instantaneous events. The PROV method is based on Lamport's (1978) notion of logical clocks to avoid synchronization issues in distributed systems.

Another form of data provenance is version-controlled data, in which revisions or updates are captured as snapshots of a dataset at a particular moment. Snapshots are ordered in relative, rather than absolute, time. Many version-control systems calculate or store differences between versions, accompanied with comments on how they vary. Version control may capture the existence of multiple instances of a dataset, but not capture, at least in a structured fashion, the processes that lead to the changes between datasets. While such temporal mechanisms are useful in data stewardship, they may not provide sufficient granularity for reusers to determine how, why, or whether multiple versions exist. An important example occurs in digital object identifiers (DOI) in which multiple versions of an object (such as a dataset or journal article) may be subsumed under a single DOI that references the most recent version (DOI Foundation, 2023).

Temporal relationships within and between datasets are difficult to document or to represent (Drucker, 2009). The examples above are but a few of the ways in which data provenance records, as a form of metadata, can aid prospective reusers in situating data, identifying contexts in which data were collected, and thus bridge some of the temporal gaps between creators and reusers. When reusers obtain datasets that are recent in origin, time-stamp conventions may be familiar, for example. Over time, it may become difficult to determine whether time stamps refer to Coordinated Universal Time (UTC), local time zones, or to assess the degree of accuracy in relative or absolute time. While climate modelers are meticulous in their analyses, the longer and more geographically diverse the datasets on which they rely, the greater the degree of uncertainty they must address (Edwards, 2010).

4 Discussion

Data sharing has become normal practice in most scholarly research domains. Knowledge infrastructures accommodate data release, deposit, retrieval, and reuse to ever greater degrees. Communities are beginning to reap some of the promised benefits of data sharing for

accelerating research, transparency, and reproducibility. However, even in the best of all possible research worlds, never will it be feasible to share all data with all potential users for all purposes of reuse for indefinite periods of time. Time, labor, and funds are finite resources. Choices and tradeoffs must be made throughout the cycles of creating, sharing, stewarding, and reusing data.

Data sharing and reuse inherently involve knowledge transfers between parties who exist at some distance from each other. The greater the distance, the more difficulty that arises in knowledge transfer. We have characterized six dimensions of distance between parties from theoretical and practical perspectives. By understanding more about these dimensions, data creators can make better choices about how to manage, release, and share their data. Similarly, knowledge about distance dimensions may aid data reusers in finding, interpreting, and reusing available data – and in understanding the barriers to reusing existing data. Other stakeholders such as data archives, libraries, universities, funding agencies, and publishers, also can employ these distance dimensions in planning, priorities, and investments.

Distances between data creators and reusers are fundamentally social, embedded deeply in the methods and practices of creating knowledge within a research domain. We do not intend our division of dimensions into social and technical aspects to be read as a binary; rather, it is a mechanism to explain the socio-technical nature of these distances. In our theoretical framework, the shortest distance exists between data creators and reusers when both have common expertise in a domain, are applying the same research methods, are collaborating on a project, curating their data to the highest standards of trust and stewardship, using data for the same purposes, and reusing data contemporaneously. As any of these six constraints are relaxed, the distance increases.

Hence, as the distance increases between data creators and reuses on any of these dimensions more investments are necessary to facilitate reuse. Actual monetary costs of these investments are difficult to establish due to the wide array of data types and contexts for data creation and reuse. Our literature review identified only a few reports of specific costs and outcomes of data stewardship, as illustrated in Box 1, and several policy reports on how to identify cost components throughout data lifecycles (National Academies of Sciences, Engineering, and Medicine, 2020; Uffen & Kinkel, 2019). These cost models necessarily address the costs that can be modeled, largely the necessary infrastructure of data archiving and storage. Our focus on the socio-technical nature of data sharing and reuse draws to the fore the 'invisible work' performed by data creators, data reusers, and many other individuals throughout the life cycles of research data (Bates, 1999; Borgman, 2003; Crain et al., 2016).

5 Conclusions

Policy and practice for open scholarship are driven more strongly by the need for sharing knowledge than by the need to reuse and redeploy that knowledge. Data creators are encouraged, if not required, to make their data findable, accessible, interoperable, and reusable (FAIR) by others (Wilkinson et al., 2016). Each of these four essential principles for data sharing is aspirational. The principles are social, in that they promote certain ways of conducting and disseminating research. They also are technical, in that they suggest architectures and software that can be deployed in support of these principles.

Most arguments for the FAIR principles and related data sharing policies of funding agencies and journals are based on transparency, reproducibility, equity, trust, and similar social concerns. Some open science arguments are economic, on the grounds that better access to data will promote reuse of existing resources and avoid duplication of effort. Others are based on

commons arguments, that research products should be treated as public goods, which involves concerns for free riders and governance models.

The challenge underlying these arguments for data sharing is how to accomplish reuse of data, once they are shared. Simply releasing research data is insufficient; considerable investment is required to make them useful to others. Some shared data will be of great value to a diverse array of reusers for long periods of time. Other shared data will never by reused by anyone, ever. Core to the problem of determining what data to share and how to do so are the difficulties of evaluating what data are reused, at what rates, by whom, when, how, for what purposes, or to what effects. For those datasets in archives, downloads can be counted, but views and downloads are not equivalent to reuse. Someone may download a dataset and reuse it immediately, later, or never. Despite data citation now being technically feasible, with the advent of digital object identifiers (DOIs) assigned to datasets, adoption of data citation mechanisms by authors is minimal. Rarely do scholarly publications include references to datasets, or data creators (Borgman, 2016; Gregory et al., 2023)

Although further investigation of data reuse cases is much needed, such studies are difficult to conduct even at small scales (Borgman et al., 2019). What we do know is that data reuse often is highly individualized. Researchers identify particular needs for data for specific purposes (Faniel & Jacobsen, 2010; Mayernik et al., 2008; Pasquetto et al., 2017, 2019; Wallis et al., 2010). Data reuse is relational and situational, depending on what is available to satisfy a particular need. Thus, reuse value lies in the relationship between creator and reuser; it is not a quality inherent in the dataset. Counting reuses of individual datasets may be informative only to the extent that these relationships can be identified.

Given that researchers and other stakeholders in the research enterprise must invest in data to facilitate reuse, the question becomes *Which* investments are most likely to contribute to effective reuse? We theorize that ease of reuse is ordered roughly by our ordering of distances: domain, methods, collaboration, curation, purpose, and time. Researchers within domains such as astronomy that have extensive knowledge infrastructures, similar research methods based on common data standards and formats, common documentation practices, and large collaborations are able to reuse each other's datasets readily (Borgman & Wofford, 2021). Conversely, researchers from different domains collaborating on a common problem in biomedicine took the better part of a decade to find methods of sharing data effectively (Bafeta et al., 2020; Pasquetto, 2018). Those who wish to reuse data from other domains, for purposes other than those for which the data were created, and at much earlier points in time, first should recognize the number of rivers they will need to cross. Some of these rivers can be bridged by technical means, such as working in portable software languages and employing interoperability interfaces where they exist. Other rivers can be bridged only by social means, such as establishing a new collaboration with the data creators, if they are still available and agree (Pasquetto et al., 2019).

Our theoretical model of the six dimensions of distance between data creators and reusers leads to the following recommendations for four groups of stakeholders: data creators, data reusers, archives, and funding agencies.

5.1 Recommendations to Data Creators

Our recommendations to data creators are to **identify the audience – the potential reusers – of your data as clearly, and as early in the research process, as possible**. A simple starting point is to consider prospective reusers at shortest distance from your work and the project at hand. Think of this audience as potential collaborators, and consider what knowledge of the research domain and of your research methods is necessary to reuse your data or to replicate your work. If your research practices build upon commonly available infrastructure of your domain, if your methods are relatively standard for the field, and your collaborations employ common data formats, then documenting your data for these audiences may be fairly straightforward.

The greater the distance you are from prospective reusers of your data, the more investment that may be necessary to share your data. If you wish to reach an audience in other domains, that relies on different infrastructures, uses different methods and tools, or different data formats, then consider employing interface tools that can bridge gaps between data formats and other technical methods that promote portability across infrastructures. The more innovative your methods, tools, software, and instrumentation, the more documentation for reuse that may be required. Similarly, to make data reusable for longer time frames, provide more provenance information. Hardware, software, instrumentation, and tools associated with digital data do not age well. Datasets that are migrated regularly to current environments will remain useful for longer; resurrecting datasets left untouched for a few years becomes increasingly difficult.

5.2 Recommendations to Data Reusers

Our recommendations to prospective data reusers **are to consider where you reside on each of the six dimensions of distance.** The shorter your distance to the origin of data, the more likely you are to find datasets to access, open, manipulate, and interpret, and that may be interoperable with your current technical environments. Thus, reusing data produced recently by current collaborators using the same methods and infrastructure, with adequate documentation, may be straightforward. In domains such as astronomy and genomics, which have extensive knowledge infrastructures for creating, sharing, and reusing data with standardized data formats and tools is normal practice. However, even in these fields, making sense of data produced a decade earlier can be difficult.

Given that data reuse is a form of knowledge transfer from the data creators, any act of data reuse will involve considerable learning about the origins of the data. Learning may involve reading literature, obtaining software and instrumentation, hiring staff with appropriate skills, or contacting the data creators who have the most intimate knowledge of their origins. Transferring knowledge of innovative methods may require 'magic hands,' whereas data exchange in areas where data and tools become 'kits' is common practice (Hilgartner & Brandt-Rauf, 1994). Magic bullets of interoperability are unlikely to be invented. Data reuse is an inherently messy and labor-intensive endeavor (Mayer-Schonberger & Cukier, 2013).

5.3 Recommendations to Data Archivists

Our recommendations to data archivists are both to **'know thy user' and to recognize how difficult it may be to know enough about your data contributors and data retrievers to bridge the distances**. Domain-specific archives, whether in astronomy or art history, are in the strongest position to construct coherent collections and to know their user communities. The curation services provided by domain archives are essential to knowledge transfer between data creators and reusers. Toward sustaining and improving curation services, these archives can **attend to documenting as much information as possible along each of these distance dimensions and their technical aspects**: infrastructure components of the domain on which data interpretation depends; methods and technical standards associated with a dataset; collaborative project or research center and associated data formats; documentation provided by contributors plus supplemental curation by the archive; purposes for which data were created and any known interfaces between tools or environments; and time frame of data creation with as much provenance information as can be obtained.

This recommendation for more documentation **argues for a careful selection procedure by archives**. Explicit tradeoffs may be necessary between acquiring greater volumes of data and investing in more extensive curation of fewer datasets.

While we are recommending more metadata than is usually provided for individual datasets, and recognizing that metadata creation is expensive, these recommendations also can be applied to guidance for self-curation by data contributors. Generic data archives such as institutional repositories rely almost entirely on self-curation by data creators who contribute datasets for longer term storage and stewardship. These data archives may not be able to invest in curation of individual datasets, **but they can offer instruction and guidance in how best to curate datasets to improve the abilities of others to reuse them**.

5.4 Recommendations to Research Funding Agencies

Our recommendations to research funding agencies are manifold. Funding agency policies focus primarily on data sharing, placing responsibility for data release on the principal investigators of grants. While releasing data is prerequisite to reuse, we recommend greater emphasis on data reuse, and on more wholistic approaches to building the infrastructures and relationships between stakeholders necessary to bridge the distances between data creators and prospective data reusers. A good start is to **recognize that 'it takes a village to share data'** and that better partnerships within and between universities are needed (Borgman & Bourne, 2022; Borgman & Brand, 2022). Additionally, funding calls could ask principal investigators to **identify intended reusers of their data** and the corresponding investments needed to bridge these distances.

We recommend further support to address the gap in knowledge about which activities lead to data reuse. Here, further empirical evidence and rich qualitative studies are warranted.

Funding agencies in the U.S. and Europe, which are the communities we know best, are investing in research methods, in collaborations, and in each of the technical areas necessary to bridge these distances, albeit more within than between domains. We recommend a broader focus on the human infrastructure necessary to support the knowledge infrastructures necessary for effective data exchange.

5.5 Future work

Data creation, sharing, and reuse are inherently social processes. All rely on knowledge infrastructures, which in turn are complex and evolving. Many stakeholders are involved in each of these processes, not only the data creators and reusers, but archives, universities, funding agencies, publishers, policy makers, and private entities involved in research enterprise. The human infrastructure involved in data sharing and the technologies involved in making data FAIR (Wilkinson et al., 2016) have received the most attention, both in terms of policy and research. Research on how, when, and why to reuse data deserves far more research attention. Never will it be possible to share all data, all the time, for all possible purposes, with all possible audiences. Hard choices must be made. Some data have high reuse value and are worthy of high

investment. Other data may be of little value beyond the initial project in which they were created and thus worthy of minimal investment.

By developing the construct of distance between data creator and data reuser our aim is to provoke new research questions, new research, and new investment, in effective and efficient circulation of research data.

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