OPINION ARTICLE

Best practice data life cycle approaches for the life sciences
[version 1; peer review: 2 approved with reservations]

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Abstract
Throughout history, the life sciences have been revolutionised by technological advances; in our era this is manifested by advances in instrumentation for data generation, and consequently researchers

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now routinely handle large amounts of heterogeneous data in digital formats. The simultaneous transitions towards biology as a data science and towards a 'life cycle' view of research data pose new challenges. Researchers face a bewildering landscape of data management requirements, recommendations and regulations, without necessarily being able to access data management training or possessing a clear understanding of practical approaches that can assist in data management in their particular research domain.

Here we provide an overview of best practice data life cycle approaches for researchers in the life sciences/bioinformatics space with a particular focus on 'omics' datasets and computer-based data processing and analysis. We discuss the different stages of the data life cycle and provide practical suggestions for useful tools and resources to improve data management practices.

**Keywords**
data sharing, data management, open science, bioinformatics, reproducibility

This article is included in the International Society for Computational Biology Community Journal gateway.

This article is included in the Agriculture, Food and Nutrition gateway.

This article is included in the Research on Research, Policy & Culture gateway.

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**Introduction**

Technological data production capacity is revolutionising biology\(^1\), but is not necessarily correlated with the ability to efficiently analyse and integrate data, or with enabling long-term data sharing and reuse. There are selfish as well as altruistic benefits to making research data reusable\(^2\): it allows one to find and reuse one’s own previously-generated data easily; it is associated with higher citation rates\(^3\); and it ensures eligibility for funding from and publication in venues that mandate data sharing, an increasingly common requirement (e.g. Final NIH statement on sharing research data, Wellcome Trust policy on data management and sharing, Bill & Melinda Gates Foundation open access policy). Currently we are losing data at a rapid rate, with up to 80% unavailable after 20 years\(^4\). This affects reproducibility - assessing the robustness of scientific conclusions by ensuring experiments and findings can be reproduced - which underpins the scientific method. Once access to the underlying data is lost, replicability, reproducibility and extensibility\(^5\) are reduced.

At a broader societal level, the full value of research data may go beyond the initial use case in unforeseen ways\(^6\), so ensuring data quality and reusability is crucial to realising its potential value\(^7\). The recent publication of the FAIR principles\(^8\) identifies four key criteria for high-quality research data: the data should be Findable, Accessible, Interoperable and Reusable. Whereas a traditional view of data focuses on collecting, processing, analysing data and publishing results only, a life cycle view reveals the additional importance of finding, storing and sharing data\(^1\). Throughout this article, we present a researcher-focused data life cycle framework that has commonalities with other published frameworks [e.g. the DataONE Data Life Cycle, the US geological survey science data lifecycle model and \(^{11,14-17}\)], but is aimed at life science researchers specifically (Figure 1).

Learning how to find, store and share research data is not typically an explicit part of undergraduate or postgraduate training in the biological sciences\(^16-17\). The scope, size and complexity of datasets in many fields has increased dramatically over the last 10–20 years, but the knowledge of how to manage this data is currently limited to specific cohorts of ‘information managers’ (e.g. research data managers, research librarians, database curators and IT professionals with expertise in databases and data schemas\(^18\)).

In response to institutional and funding requirements around data availability, a number of tools and educational programs have been developed to help researchers create Data Management Plans to address elements of the data lifecycle\(^19\); however, even when a plan is mandated, there is often a gap between the plan and the actions of the researcher\(^20\).

During the week of 24–28 October 2016, EMBL Australia Bioinformatics Resource (EMBL-ABR)\(^26\) led workshops on the data life cycle for life science researchers working in the plant, animal, microbial and medical domains. The workshops provided opportunities to (i) map the current approaches to the data life cycle in biology and bioinformatics, and (ii) present and discuss best practice approaches and standards for key international projects with Australian life scientists and bioinformaticians. Discussions during these workshops have informed this publication, which targets life science researchers wanting to improve their data management practice; throughout we highlight some specific data management challenges mentioned by participants.

An earlier version of this article can be found on bioRxiv (https://doi.org/10.1101/167619).

**Finding data**

In biology, research data is frequently published as supplementary material to articles, on personal or institutional websites, or in non-discipline-specific repositories like FigShare and Dryad\(^21\). In such cases, data may exist behind a paywall, there is no guarantee it will remain extant, and, unless one already knows it exists and its exact location, it may remain undiscovered\(^22\). It is only when a dataset is added to public data repositories, along with accompanying standardized descriptive metadata (see Collecting data), that it can be indexed and made publicly available\(^23\). Data repositories also provide unique identifiers that increase findability by enabling persistent linking from other locations and permanent association between data and its metadata.

In the field of molecular biology, a number of bioinformatics-relevant organisations host public data repositories. National and international-level organisations of this kind include the European Bioinformatics Institute (EMBL-EBI)\(^3\), the National Centre for Biotechnology Information (NCBI)\(^25\), the DNA Data Bank of Japan

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**Figure 1.** The Data Life Cycle framework for bioscience, biomedical and bioinformatics data that is discussed throughout this article. Black arrows indicate the ‘traditional’, linear view of research data; the green arrows show the steps necessary for data reusability. This framework is likely to be a simplified representation of any given research project, and in practice there would be numerous ‘feedback loops’ and revisiting of previous stages. In addition, the publishing stage can occur at several points in the data life cycle.
Numerous repositories are available for biological data (see Table 1 for an overview), though repositories are still lacking for some data types and sub-domains. Many specialised data repositories exist outside of the shared central infrastructure mentioned, often run voluntarily or with minimal funding. Support for biocuration, hosting and maintenance of these smaller-scale but key resources is a pressing problem. The quality of the user-submitted data in public repositories can mean that public datasets require extra curation before reuse. Unfortunately, due to low uptake of established methods (see the EMBL-EBI and NCBI third-party annotation policies and) to correct the data, the results of extra curation may not find their way back into the repositories. Repositories are often not easily searched by generic web search engines. Registries, which form a secondary layer linking multiple, primary repositories, may offer a more convenient way to search across multiple repositories for data relevant to a researcher’s topics of interest.

Collecting data
The most useful data has associated information about its creation, its content and its context - called metadata. If metadata is well structured, uses consistent element names and contains element values with specific descriptions from agreed-upon vocabularies, it enables machine readability, aggregation, integration and tracking across datasets: allowing for Findability, Interoperability and Reusability. One key approach in best-practice metadata collection is to use controlled vocabularies built from ontology terms. Biological ontologies are tools that provide machine-interpretable representations of some aspect of biological reality. They are a way of organising and defining objects (i.e. physical entities or processes), and the relationships between them. Sourcing metadata element values from ontologies ensures that the terms used in metadata are consistent and clearly defined. There are several user-friendly tools available to assist researchers in accessing, using and contributing to ontologies (Table 2).

Adopting standard data and metadata formats and syntax is critical for compliance with FAIR principles. Biological and biomedical research has been considered an especially challenging research field in this regard, as datatypes are extremely heterogeneous and not all have defined data standards; many existing data standards are complex and therefore difficult to use, or only informally defined, and therefore subject to variation, misrepresentation, and divergence over time. Nevertheless, well-established standards exist for a variety of biological data types (Table 3). FAIRsharing is a useful registry of data standards and policies that also indicates the current status of standards for different data types and those recommended by databases and research organisations.

Most public repositories for biological data (see Table 1 and Storing data section) require that minimum metadata be submitted accompanying each dataset (Table 4). This minimum metadata specification typically has broad community input. Minimum metadata standards may not include the crucial metadata fields that give the full context of the particular research project, so it is important to gather metadata early, understand how to extend a minimum metadata template to include additional fields in a structured way, and think carefully about all the relevant pieces of metadata information that might be required for reuse.

Processing and analysing data
Recording and reporting how research data is processed and analysed computationally is crucial for reproducibility and assessment of research quality. Full reproducibility requires access to the software, software versions, dependencies and operating system used as well as the data and software code itself. Therefore, although computational work is often seen as enabling reproducibility in the short term, in the long term it is fragile and reproducibility is limited (e.g. discussion by D. Katz, K. Hinsen and C.T. Brown). Best-practice approaches for preserving data processing and analysis code involve hosting source code in a repository where it receives a unique identifier and is under version control; where it is open, accessible, interoperable and reusable - broadly mapping to the FAIR principles for data. Github and Bitbucket, for example, fulfill these criteria, and Zenodo additionally generates Digital Object Identifiers (DOIs) for submissions and guarantees long-term archiving. Several recent publications have suggested ways to improve current practice in research software development.

The same points hold for wet-lab data production: for full reproducibility, it is important to capture and enable access to specimen cell lines, tissue samples and/or DNA as well as reagents. Wet-lab methods can be captured in electronic laboratory notebooks and reported in the Biosamples database, protocols.io or OpenWetWare; specimens can be lodged in biobanks, culture or museum collections; but the effort involved in enabling full reproducibility remains extensive. Electronic laboratory notebooks are frequently suggested as a sensible way to make this information openly available and archived. Some partial solutions exist (e.g. LabTrove, BlogMyData, Benchling and others), including tools for specific domains such as the Scratchpad Virtual Research Environment for natural history research. Other tools can act as or be combined to produce notebooks for small standalone code-based projects (Boettiger, 2017 and update), including Jupyter Notebook, Rmarkdown, and Docker. However, it remains a challenge to implement online laboratory notebooks to cover both field/lab work and computer-based work, especially when computer work is extensive, involved and non-modular. Currently, no best-practice guidelines or minimum information standards exist for use of electronic laboratory notebooks. We suggest that appropriate minimum information to be recorded for most computer-based tasks should include
<table>
<thead>
<tr>
<th>Database/register</th>
<th>Name</th>
<th>Description</th>
<th>Datatypes</th>
<th>URL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Database</td>
<td>Gene Ontology</td>
<td>Repository of functional roles of gene products, including proteins, ncRNAs, and complexes.</td>
<td>Functional roles as determined experimentally or through inference, including evidence for these roles and links to literature</td>
<td><a href="http://geneontology.org">http://geneontology.org</a></td>
</tr>
<tr>
<td>Database</td>
<td>OrthoDB</td>
<td>Repository for gene ortholog information</td>
<td>Protein sequences and orthologous group annotations for evolutionarily related species groups</td>
<td><a href="http://www.orthodb.org">http://www.orthodb.org</a></td>
</tr>
<tr>
<td>Database</td>
<td>eggNOG</td>
<td>Repository for gene ortholog information with functional annotation prediction tool</td>
<td>Protein sequences, orthologous group annotations and phylogenetic trees for evolutionarily related species groups</td>
<td><a href="http://eggnogdb.embl.de">http://eggnogdb.embl.de</a></td>
</tr>
<tr>
<td>Database</td>
<td>European Nucleotide Archive (ENA)</td>
<td>Repository for nucleotide sequence information</td>
<td>Raw next-generation sequencing data, genome assembly and annotation data</td>
<td><a href="http://www.ebi.ac.uk/ena">http://www.ebi.ac.uk/ena</a></td>
</tr>
<tr>
<td>Database</td>
<td>ArrayExpress</td>
<td>Repository for genomic expression data</td>
<td>RNA-seq, microarray, CHIP-seq, Basi-seq and more (see <a href="https://www.ebi.ac.uk/arrayexpress/help/experiment_types.htm">https://www.ebi.ac.uk/arrayexpress/help/experiment_types.htm</a> for full list)</td>
<td><a href="https://www.ebi.ac.uk/arrayexpress">https://www.ebi.ac.uk/arrayexpress</a></td>
</tr>
<tr>
<td>Database</td>
<td>PRIDE</td>
<td>Repository for proteomics data</td>
<td>Annotated protein sequences</td>
<td><a href="https://www.ebi.ac.uk/pride/archive">https://www.ebi.ac.uk/pride/archive</a></td>
</tr>
<tr>
<td>Database</td>
<td>Protein Data Bank (PDB)</td>
<td>Repository for protein structure information</td>
<td>3D structures of proteins, nucleic acids and complexes</td>
<td><a href="https://www.wwpdb.org">https://www.wwpdb.org</a></td>
</tr>
<tr>
<td>Database</td>
<td>MetaboLights</td>
<td>Repository for metabolomics experiments and derived information</td>
<td>Metabolite structures, reference spectra and biochemical characteristics, raw and processed metabolite profiles</td>
<td><a href="http://www.ebi.ac.uk/metabolights">http://www.ebi.ac.uk/metabolights</a></td>
</tr>
<tr>
<td>Database</td>
<td>ChEBI</td>
<td>Ontology and repository for chemical entities</td>
<td>Small molecule structures and chemical properties</td>
<td><a href="https://www.ebi.ac.uk/chebi">https://www.ebi.ac.uk/chebi</a></td>
</tr>
<tr>
<td>Database</td>
<td>BioStudies</td>
<td>Repository for descriptions of biological studies, with links to data in other databases and publications</td>
<td>Taxonomic classification and nomenclature data for organisms in public NCBI databases</td>
<td><a href="https://www.ebi.ac.uk/biostudies">https://www.ebi.ac.uk/biostudies</a></td>
</tr>
</tbody>
</table>

Table 1. Overview of some representative databases, registries and other tools to find life science data.
<table>
<thead>
<tr>
<th>Database/registry</th>
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<th>Description</th>
<th>Datatypes</th>
<th>URL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Database</td>
<td>Database</td>
<td>Repository for information about biological samples, with links to data generated from these samples located in other databases</td>
<td>Sample descriptions</td>
<td><a href="https://www.ebi.ac.uk/biosamples/">https://www.ebi.ac.uk/biosamples/</a></td>
</tr>
<tr>
<td>with analysis</td>
<td>layer</td>
<td>Repository for molecular interaction information</td>
<td>Molecular interactions and evidence type</td>
<td><a href="http://www.intact.org/">http://www.intact.org/</a></td>
</tr>
<tr>
<td>Database</td>
<td>UniProtKB</td>
<td>Repository for protein sequence and function data. Combines curated (UniProtKB/SwissProt) and automatically annotated, uncurated (UniProtKB/TrEMBL) databases</td>
<td>Raw, processed and/or analysed sequence and genotype data along with phenotype information</td>
<td><a href="https://www.uniprot.org/">https://www.uniprot.org/</a></td>
</tr>
<tr>
<td>with analysis</td>
<td>layer</td>
<td>Repository and analysis service for the proteomics data.</td>
<td>Protein sequences, protein function and evidence type</td>
<td><a href="http://www.mg-raft.de/">http://www.mg-raft.de/</a></td>
</tr>
<tr>
<td>Database</td>
<td>European Genome-phenome Archive</td>
<td>Repository and analysis service for the genomics data.</td>
<td>Genomic, transcriptomic, proteomic and metabolomic data</td>
<td><a href="https://www.ebi.ac.uk/ega/">https://www.ebi.ac.uk/ega/</a></td>
</tr>
<tr>
<td>Database</td>
<td>EBI</td>
<td>Repository and analysis service for metagenomics data.</td>
<td>Genomic, transcriptomic, proteomic and metabolomic data</td>
<td><a href="http://www.ebi.ac.uk/metagenomics/">http://www.ebi.ac.uk/metagenomics/</a></td>
</tr>
<tr>
<td>Database</td>
<td>MG-RAST</td>
<td>Repository and analysis service for metagenomics data.</td>
<td>Genomic, transcriptomic, proteomic and metabolomic data</td>
<td><a href="http://metagenomics.anl.gov/">http://metagenomics.anl.gov/</a></td>
</tr>
<tr>
<td>Registry</td>
<td>Omics DI</td>
<td>Registry for research data repositories across multiple research disciplines</td>
<td>Information on databases, standards and policies including fields of research and usage recommendations by key organisations</td>
<td><a href="https://biosharing.org/">https://biosharing.org/</a></td>
</tr>
<tr>
<td>Registry</td>
<td>DataMed</td>
<td>Registry for research data repositories across multiple research disciplines</td>
<td>Information on databases, standards and policies</td>
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</tr>
<tr>
<td>Registry</td>
<td>Biosharing</td>
<td>Registry for research data repositories across multiple research disciplines</td>
<td>Information on databases, standards and policies</td>
<td><a href="https://biosharing.org/">https://biosharing.org/</a></td>
</tr>
<tr>
<td>Registry</td>
<td>re3data</td>
<td>Registry for research data repositories across multiple research disciplines</td>
<td>Information on databases, standards and policies</td>
<td><a href="https://www.re3data.org/">https://www.re3data.org/</a></td>
</tr>
</tbody>
</table>
date, task name and brief description, aim, actual command(s) used, software names and versions used, input/output file names and locations, script names and locations.

During the EMBL-ABR workshop series, participants identified the data processing and analysis stage as one of the most challenging for openness. A few participants had put intensive individual effort into developing custom online lab (and code) notebook approaches, but the majority had little awareness of this as a useful goal. This suggests a gap between modern biological research as a field of data science, and biology as it is still mostly taught in undergraduate courses, with little or no focus on computational analysis, or project or data management. As reported elsewhere,[16–18] this gap has left researchers lacking key knowledge and skills required to implement best practices in dealing with the life cycle of their data.

Publishing data

Traditionally, scientific publications included raw research data, but in recent times datasets have grown beyond the scope of practical inclusion in a manuscript.[11,44] Selected data outputs are often included without sharing or publishing the underlying raw data[14]. Journals increasingly recommend or require deposition of raw data in a public repository [e.g. 59], although exceptions have been made for publications containing commercially-relevant data[60]. The current data-sharing mandate is somewhat field-dependent[61] and also varies within fields[62]. For example, in the field of bioinformatics, the UPSIDE principle[63] is referred to by some journals (e.g. Bioinformatics), while others have journal- or publisher-specific policies (e.g. BMC Bioinformatics).

The vast majority of scientific journals require inclusion of processing and analysis methods in ‘sufficient detail for reproduction’ (e.g. Public Library of Science submission and data availability guidelines; International Committee of Medical Journal Editors manuscript preparation guidelines; Science instructions for authors; Elsevier Cell Press STAR Methods; and[64]), though journal requirements are diverse and complex[65], and the level of detail authors provide can vary greatly in practice[66,67]. More recently, many authors have highlighted that full reproducibility requires sharing data and resources at all stages of the scientific process, from raw data (including biological samples) to full methods and analysis workflows[16,53,67]. However, this remains a challenge[68,69], as discussed in the Processing and analysing data section. To our knowledge, strategies for enabling computational reproducibility are currently not mandated by any scientific journal.

A recent development in the field of scientific publishing is the establishment of ‘data journals’: scientific journals that publish papers describing datasets. This gives authors a vehicle to accrue citations (still a dominant metric of academic impact) for data production alone, which can often be labour-intensive and expensive yet is typically not well recognised under the traditional publishing model. Examples of this article type include the Data Descriptor in Scientific Data and the Data Note in GigaScience, which do not include detailed new analysis but rather focus on describing and enabling reuse of datasets.

The movement towards sharing research publications themselves (‘Open Access Publishing’) has been discussed extensively elsewhere [e.g. 22,70,71]. Publications have associated metadata (creator, date, title etc.; see Dublin Core Metadata Initiative metadata terms) and unique identifiers (PubMed ID for biomedical and some life science journals, DOIs for the vast majority of journals; see Table 5). The ORCID system enables researchers to claim their own unique identifier, which can be linked to their publications. The use of unique identifiers within publications referring to repository records (e.g. genes, proteins, chemical entities) is not generally mandated by journals, although it would ensure a common vocabulary is used and so make scientific results more interoperable and reusable[72]. Some efforts are underway to make this easier for researchers: for example, Genetics and other Genetics Society of America journals assist authors in linking gene names to model organism database entries.

Storing data

While primary data archives are the best location for raw data and some downstream data outputs (Table 1), researchers also need local data storage solutions during the processing and analysis stages. Data storage requirements vary among research domains, with major challenges often evident for groups working on taxa with large genomes (e.g. crop plants), which require large storage resources, or on human data, where privacy regulations may require local data storage, access controls and conversion to
<table>
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<th>Data type</th>
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<th>Description</th>
<th>Reference or URL for format specification</th>
<th>URLs for repositories accepting data in this format</th>
</tr>
</thead>
<tbody>
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<td>FASTA</td>
<td>FASTA is a common text format to store DNA/RNA/Protein sequence. and FASTQ combines base quality information with the nucleotide sequence. HDF5 is a newer sequence read formats used by long read sequencers e.g. PacBio and Oxford Nanopore. Raw sequence can also be stored in unaligned SAM/BAM/CRAM format</td>
<td>41</td>
<td><a href="https://support.hdfgroup.org/HDF5/">https://support.hdfgroup.org/HDF5/</a> <a href="https://samtools.github.io/hts-specs/">https://samtools.github.io/hts-specs/</a></td>
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<td></td>
<td>SAM/BAM/CRAM</td>
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<td><a href="http://www.ensembl.org/info/website/upload/gff.htm">http://www.ensembl.org/info/website/upload/gff.htm</a></td>
</tr>
<tr>
<td>Assembled DNA sequence</td>
<td>FASTA</td>
<td>Assemblies without annotation are generally stored in FASTA format. Annotation can be integrated with assemblies in contig, scaffold or chromosome flat file format. AGP files are used to describe how smaller fragments are placed in an assembly but do not contain the sequence information themselves</td>
<td>41</td>
<td><a href="http://www.ebi.ac.uk/ena/submit/contig-flat-file">http://www.ebi.ac.uk/ena/submit/contig-flat-file</a> <a href="http://www.ebi.ac.uk/ena/submit/scaffold-flat-file">http://www.ebi.ac.uk/ena/submit/scaffold-flat-file</a> <a href="https://www.ncbi.nlm.nih.gov/assembly/agp/AGP_Specification/">https://www.ncbi.nlm.nih.gov/assembly/agp/AGP_Specification/</a></td>
</tr>
<tr>
<td></td>
<td>Flat file</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>AGP</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aligned DNA sequence</td>
<td>SAM/BAM</td>
<td>Sequences aligned to a reference are represented in sequence alignment and mapping format (SAM). Its binary version is called BAM and further compression can be done using the CRAM format</td>
<td><a href="https://samtools.github.io/hts-specs/">https://samtools.github.io/hts-specs/</a></td>
<td><a href="https://www.ncbi.nlm.nih.gov/sra/docs/submitformats/#bam">https://www.ncbi.nlm.nih.gov/sra/docs/submitformats/#bam</a></td>
</tr>
<tr>
<td></td>
<td>CRAM</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gene model or genomic feature annotation</td>
<td>GTF/GFF/GFF3</td>
<td>General feature format or general transfer format are commonly used to store genomic features in tab-delimited flat text format. GFF3 is a more advanced version of the basic GFF that allows description of more complex features. BED format is a tab-delimited text format that also allows definition of how a feature should be displayed (e.g. on a genome browser). GenBank flat file Format (GB/GBK) is also commonly used but not well standardised</td>
<td><a href="https://github.com/The-Sequence-Ontology/Specifications/blob/master/gf3.md">https://github.com/The-Sequence-Ontology/Specifications/blob/master/gf3.md</a> <a href="https://genome.ucsc.edu/FAQ/FAQformat.html">https://genome.ucsc.edu/FAQ/FAQformat.html</a> <a href="https://genome.ucsc.edu/FAQ/FAQformat.html">https://genome.ucsc.edu/FAQ/FAQformat.html</a> <a href="https://www.ncbi.nlm.nih.gov/Sitemap/samplerecord.html">https://www.ncbi.nlm.nih.gov/Sitemap/samplerecord.html</a></td>
<td><a href="http://www.ensembl.org/info/website/upload/gff.html">http://www.ensembl.org/info/website/upload/gff.html</a> <a href="http://www.ensembl.org/info/website/upload/gff3.html">http://www.ensembl.org/info/website/upload/gff3.html</a></td>
</tr>
<tr>
<td>Data type</td>
<td>Format name</td>
<td>Description</td>
<td>Reference or URL for format specification</td>
<td>URLs for repositories accepting data in this format</td>
</tr>
<tr>
<td>---------------------------</td>
<td>-------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
<td>----------------------------------------------------------------------------------</td>
<td>---------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Gene functional annotation</td>
<td>GAF</td>
<td>A GAF file is a GO Annotation File containing annotations made to the GO by a contributing resource such as FlyBase or Pombase. However, the GAF standard is applicable outside of GO, e.g. using other ontologies such as PO. GAF (v2) is a simple tab-delimited file format with 17 columns to describe an entity (e.g. a protein), its annotation and some annotation metadata</td>
<td><a href="http://geneontology.org/page/go-annotation-file-format-2">http://geneontology.org/page/go-annotation-file-format-2</a></td>
<td><a href="http://geneontology.org/page/submitting-go-annotations">http://geneontology.org/page/submitting-go-annotations</a></td>
</tr>
<tr>
<td>Genetic/genomic variants</td>
<td>VCF</td>
<td>A tab-delimited text format to store meta-information as header lines followed by information about variants position in the genome. The current version is VCF4.2</td>
<td><a href="https://samtools.github.io/hts-specs/VCFv4.2.pdf">https://samtools.github.io/hts-specs/VCFv4.2.pdf</a></td>
<td><a href="http://www.ensembl.org/info/website/upload/var.htm">http://www.ensembl.org/info/website/upload/var.htm</a></td>
</tr>
<tr>
<td>Interaction data</td>
<td>PSI-MI XML</td>
<td>Data formats developed to exchange molecular interaction data, related metadata and fully describe molecule constructs</td>
<td><a href="http://psidev.info/groups/molecular-interactions">http://psidev.info/groups/molecular-interactions</a></td>
<td><a href="http://www.ebi.ac.uk/intact">http://www.ebi.ac.uk/intact</a></td>
</tr>
<tr>
<td>Interaction data</td>
<td>MITAB</td>
<td>Data formats developed to exchange molecular interaction data, related metadata and fully describe molecule constructs</td>
<td><a href="http://psidev.info/groups/molecular-interactions">http://psidev.info/groups/molecular-interactions</a></td>
<td><a href="http://www.ebi.ac.uk/intact">http://www.ebi.ac.uk/intact</a></td>
</tr>
<tr>
<td>Raw metabolite profile</td>
<td>mzML</td>
<td>XML based data formats that define mass spectrometry and nuclear magnetic resonance raw data in Metabolomics</td>
<td><a href="http://www.psidev.info/mzml">http://www.psidev.info/mzml</a></td>
<td></td>
</tr>
<tr>
<td>Raw metabolite profile</td>
<td>nmrML</td>
<td>XML based data formats that define mass spectrometry and nuclear magnetic resonance raw data in Metabolomics</td>
<td><a href="http://nmrml.org/">http://nmrml.org/</a></td>
<td></td>
</tr>
<tr>
<td>Protein sequence</td>
<td>FASTA</td>
<td>A text-based format for representing nucleotide sequences or protein sequences, in which nucleotides or amino acids are represented using single-letter codes</td>
<td>41</td>
<td><a href="http://www.uniprot.org">www.uniprot.org</a></td>
</tr>
<tr>
<td>Raw proteome profile</td>
<td>mzML</td>
<td>A formally defined XML format for representing mass spectrometry data. Files typically contain sequences of mass spectra, plus metadata about the experiment</td>
<td><a href="http://www.psidev.info/mzml">http://www.psidev.info/mzml</a></td>
<td><a href="http://www.ebi.ac.uk/pride">www.ebi.ac.uk/pride</a></td>
</tr>
<tr>
<td>Organisms and specimens</td>
<td>Darwin Core</td>
<td>The Darwin Core (DwC) standard facilitates the exchange of information about the geographic location of organisms and associated collection specimens</td>
<td><a href="http://rs.tdwg.org/dwc/">http://rs.tdwg.org/dwc/</a></td>
<td></td>
</tr>
<tr>
<td>Name</td>
<td>Description</td>
<td>Examples of projects/databases that use this specification</td>
<td>URL</td>
<td></td>
</tr>
<tr>
<td>------</td>
<td>-------------</td>
<td>----------------------------------------------------------</td>
<td>-----</td>
<td></td>
</tr>
<tr>
<td>MINSEQE</td>
<td>Minimum Information about a high-throughput SEQuencing Experiment</td>
<td>Developed by the Functional Genomics Data Society. Used in the NCBI Sequence Read Archive, ArrayExpress</td>
<td><a href="http://fged.org/site_media/pdf/MINSEQE_1.0.pdf">http://fged.org/site_media/pdf/MINSEQE_1.0.pdf</a></td>
<td></td>
</tr>
<tr>
<td>MIMIx</td>
<td>Minimum Information about a Molecular Interaction eXperiment</td>
<td>Developed by the Proteomics Standards Initiative. Adopted by the IMEx Consortium databases</td>
<td><a href="http://www.psidev.info/mimix">http://www.psidev.info/mimix</a></td>
<td></td>
</tr>
<tr>
<td>MIAPE</td>
<td>Minimum Information About a Proteomics Experiment</td>
<td>Developed by the Proteomics Standards Initiative. Adopted by PRIDE, World-2DPAGE and ProteomeXchange databases</td>
<td><a href="http://www.psidev.info/miapex">http://www.psidev.info/miapex</a></td>
<td></td>
</tr>
</tbody>
</table>
| Metabolomics Standards Initiative (MSI) standards | Minimal reporting structures that represent different parts of the metabolomics workflow | Developed by the Metabolomics Standards Initiative (MSI) and the Coordination of Standards in Metabolomics (COSMOS) consortium | [http://www.metabolomics-msi.org/](http://www.metabolomics-msi.org/)
<p>| MIRIAM | Minimal Information Required In the Annotation of Models. For annotation and curation of computational models in biology | Initiated by the BioModels.net effort. Adopted by the EBI BioModels database and others | <a href="http://co.mbine.org/standards/miriam">http://co.mbine.org/standards/miriam</a> |</p>
<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Examples of projects/databases that use this specification</th>
<th>URL</th>
</tr>
</thead>
<tbody>
<tr>
<td>MDM</td>
<td>Minimal Data for Mapping for sample and experimental metadata for pathogen genome-scale sequence data</td>
<td>Developed by the Global Microbial Identifier Initiative and EBI. Complies with EBI ENA database submission requirements</td>
<td><a href="http://www.ebi.ac.uk/ena/submit/pathogen-data">http://www.ebi.ac.uk/ena/submit/pathogen-data</a></td>
</tr>
<tr>
<td>FAANG sample metadata specification</td>
<td>Metadata specification for biological samples derived from animals (animals, tissue samples, cells or other biological materials). Complies with EBI database requirements and BioSamples database formats</td>
<td>Developed and used by the Functional Annotation of Animal Genomes Consortium</td>
<td><a href="https://github.com/FAANG/faang-metadata/blob/master/docs/faang_sample_metadata.md">https://github.com/FAANG/faang-metadata/blob/master/docs/faang_sample_metadata.md</a></td>
</tr>
<tr>
<td>FAANG experimental metadata specification</td>
<td>Metadata specification for sequencing and array experiments on animal samples</td>
<td>Developed and used by the Functional Annotation of Animal Genomes Consortium</td>
<td><a href="https://github.com/FAANG/faang-metadata/blob/master/docs/faang_experiment_metadata.md">https://github.com/FAANG/faang-metadata/blob/master/docs/faang_experiment_metadata.md</a></td>
</tr>
<tr>
<td>FAANG analysis metadata specification</td>
<td>Metadata specification for analysis results</td>
<td>Developed and used by the Functional Annotation of Animal Genomes Consortium. NB no public repository exists for this specific datatype</td>
<td><a href="https://github.com/FAANG/faang-metadata/blob/master/docs/faang_analysis_metadata.md">https://github.com/FAANG/faang-metadata/blob/master/docs/faang_analysis_metadata.md</a></td>
</tr>
<tr>
<td>SNOMED-CT</td>
<td>Medical terminology and pharmaceutical product standard</td>
<td>Commercial but collaboratively-designed product</td>
<td><a href="http://www.snomed.org/snomed-ct">http://www.snomed.org/snomed-ct</a></td>
</tr>
<tr>
<td>Name</td>
<td>Relevant stage of data life cycle</td>
<td>Description</td>
<td>URL</td>
</tr>
<tr>
<td>-------------------------------------------</td>
<td>----------------------------------</td>
<td>-----------------------------------------------------------------------------</td>
<td>----------------------------------------------------------------------</td>
</tr>
<tr>
<td>Digital Object Identifier (DOI)</td>
<td>Publishing, Sharing, Finding</td>
<td>A unique identifier for a digital (or physical or abstract) object</td>
<td><a href="https://www.doi.org/">https://www.doi.org/</a></td>
</tr>
<tr>
<td>Open Researcher and Contributor ID (ORCID)</td>
<td>Publishing</td>
<td>An identifier for a specific researcher that persists across publications and other research outputs</td>
<td><a href="https://orcid.org/">https://orcid.org/</a></td>
</tr>
<tr>
<td>Repository accession number</td>
<td>Finding, Processing/ Analyzing, Publishing, Sharing, Storing</td>
<td>A unique identifier for a record within a repository. Format will be repository-specific. Examples include NIH UIDs (unique identifiers) and accession numbers; ENA accession numbers; PDB IDs For example, <a href="https://support.ncbi.nlm.nih.gov/link/portal/28045/28049/Article/499/">https://support.ncbi.nlm.nih.gov/link/portal/28045/28049/Article/499/</a> <a href="http://www.ebi.ac.uk/ena/submit/accession-number-formats">http://www.ebi.ac.uk/ena/submit/accession-number-formats</a></td>
<td></td>
</tr>
<tr>
<td>International Standard Serial Number (ISSN)</td>
<td>Publishing</td>
<td>A unique identifier for a journal, magazine or periodical</td>
<td><a href="http://www.issn.org/">http://www.issn.org/</a></td>
</tr>
</tbody>
</table>
non-identifiable data if data is to be shared (see the Australian National Data Service de-identification guide, the National Health and Medical Research Council statement on ethical conduct in human research, and the Australian National Medical Research Storage Facility discussion paper on legal, best practice and security frameworks). In addition, long-term preservation of research data should consider threats such as storage failure, mistaken erasure, bit rot, outdated media, outdated formats, loss of context and organisational failure.

Sharing data
The best-practice approach to sharing biological data is to deposit it (with associated metadata) in a primary archive suitable for that datatype that complies with FAIR principles. As highlighted in the Storing data section, these archives assure both data storage and public sharing as their core mission, making them the most reliable location for long-term data storage. Alternative data sharing venues (e.g. FigShare, Dryad) do not require or implement specific metadata or data standards. This means that while these venues have a low barrier to entry for submitters, the data is not FAIR unless submitters have independently decided to comply with more stringent criteria. If available, an institutional repository may be a good option if there is no suitable archive for that datatype. Importantly, plans for data sharing should be made at the start of a research project and reviewed during the project, to ensure ethical approval is in place and that the resources and metadata needed for effective sharing are available at earlier stages of the data life cycle.

During the EMBL-ABR workshop series, the majority of participants were familiar with at least some public primary data repositories, and many had submitted data to them previously. A common complaint was around usability of current data submission tools and a lack of transparency around metadata requirements and the rationale for them. A few workshop participants raised specific issues about the potential limitations of public data repositories where their data departed from the assumptions of the repository (e.g. unusual gene models supported by experimental evidence that were rejected by the automated NCBI curation system). Most workshop participants were unaware they could provide feedback to the repositories to deal with such situations, and this could also be made clearer on the repository websites. Again, this points in part to existing limitations in the undergraduate and postgraduate training received by researchers, where the concepts presented in this article are presented as afterthoughts, if at all. On the repository side, while there is a lot of useful information and training material available to guide researchers through the submission process (e.g. the EMBL-EBI Train Online webinars and online training modules), it is not always linked clearly from the database portals or submission pages themselves. Similarly, while there are specifications and standards available for many kinds of metadata [Table 4; also see FAIRsharing], many do not have example templates available, which would assist researchers in implementing the standards in practice.

What can the research community do to encourage best practice?
We believe that the biological/biomedical community and individual researchers have a responsibility to the public to help advance knowledge by making research data FAIR for reuse, especially if the data were generated using public funding. There are several steps that can assist in this mission:

1. **Senior scientists should lead by example** and ensure all the data generated by their laboratories is well-managed, fully annotated with the appropriate metadata and made publicly available in an appropriate repository.

2. **The importance of data management and benefits of data reuse should be taught** at the undergraduate and postgraduate levels. Computational biology and bioinformatics courses in particular should include material about data repositories, data and metadata standards, data discovery and access strategies. Material should be domain-specific enough for students to attain learning outcomes directly relevant to their research field.

3. Funding bodies are already taking a lead role in this area by requiring the incorporation of a data management plan into grant applications. A next step would be for a formal check, at the end of the grant period, that this plan has been adhered to and data is available in an appropriate format for reuse.

4. **Funding bodies and research institutions should judge quality dataset generation as a valued metric when evaluating grant or promotion applications.**

5. Similarly, leadership and participation in community efforts in data and metadata standards, and open software and workflow development should be recognised as academic outputs.

6. **Data repositories should ensure that the data deposition and third-party annotation processes are as FAIR and painless as possible** to the naive researcher, without the need for extensive bioinformatics support.

7. **Journals should require editors and reviewers to check manuscripts to ensure that all data, including research software code and samples where appropriate, have been made publicly available in an appropriate repository,** and that methods have been described in enough detail to allow re-use and meaningful reanalysis.

8. Finally, researchers reusing any data should openly acknowledge this fact and fully cite the dataset, including unique identifiers.
Conclusions

While the concept of a life cycle for research data is appealing from an Open Science perspective, challenges remain for life science researchers to put this into practice. During the EMBL-ABR Data Life Cycle workshop series, we noted limited awareness among attendees of the resources available to researchers that assist in finding, collecting, processing, analysis, publishing, storing and sharing FAIR data. We believe this article provides a useful overview of the relevant concepts and an introduction to key organisations, resources and guidelines to help researchers improve their data management practices.

Furthermore, we note that data management in the era of biology as a data science is a complex and evolving topic and both best practices and challenges are highly domain-specific, even within the life sciences. This factor may not always be appreciated at the organisational level, but has major practical implications for the quality and interoperability of shared life science data. Finally, domain-specific education and training in data management would be of great value to the life science research workforce, and we note an existing gap at the undergraduate, postgraduate and short course level in this area.

Competing interests

No competing interests were disclosed.

Grant information

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The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Acknowledgements

The authors thank Dan Bolser for his involvement in the EMBL-ABR Data Life Cycle workshops, and all workshop participants for sharing their experiences and useful discussions.

References


Page 15 of 27
Open Peer Review

Current Peer Review Status:  ?  ?

Version 1

Reviewer Report 15 December 2017

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Sven Nahnsen
Quantitative Biology Center (QBiC), University of Tübingen, Tübingen, Germany

The article “Best practice data life cycle approaches for the life sciences”, submitted by Griffin et al. reports opinions on how to best manage the growing complexity of scientific data in the life sciences.

The article touches on an extremely important topic that is currently very purely covered in the literature. In fact, data-driven approaches in the biosciences will strongly rely on professional concepts of data management. In brief, I recommend the indexing of the article, as we urgently need stronger awareness of this topic, upon the implementation of some (probably rather minor) changes to the article. The article nicely illustrates the needs in data life cycle management and also suggests best concepts to be followed by researchers. The main content of the article has been compiled based on a workshop that was attended by the authors. At some statements the article reads like the minutes of this meeting; I suggest editing the corresponding paragraphs to avoid the impression of reading meeting minutes.

I suggest the following issues to be fixed before indexing:

- Figure 1: This illustration is very important and can be used by many readers. I suggest to use figures wherever possible to replace the words such as “finding”, “integrating”, ...

- The reference to Figure 1 in the second paragraph states that it illustrates a specific aim to the life sciences. I don't see which of these points should be specific to the life science, but would rather argue that these principles are rather generic and provides a cycle for business intelligence processes in general. It might also be a good location to reference the DAMA (Data management association internation, dama.org) and specifically to the DAMA Body of Knowledge, which is one of the few references for data management and also data life cycle considerations. Further needed references should hint to the Global Alliance for Genomics and Health (ga4gh.org).

- Page 13: The paragraph on data sharing missing some discussion on authentication issues. I would like see some introduction and discussion to the OpenID concept. Especially for
medical data there need to be appropriate mechanisms to trace users, concepts for data privacy and so on. As a best practice use case for these topics, the mechanism from ICGC could be introduced.

○ The following paragraph states: “A few workshop participants...”. Rephrase, no meeting minutes..

○ I would have loved to see more use cases/examples for the individual best practices. E.g. for the data sharing the ICGC efforts could be described more thoroughly.

○ The article would benefit for 2-3 additional figures. I guess it could be a nice figure to illustrate the concept of controlled vocabularies and/or ontologies. While this seems to be trivial for bioinformaticians/computer scientists, it is not that obvious what it means to non-computer scientists; inspiration for figures can also be obtained by the data sharing mechanisms for the Global alliance for Genomics and Health

Minor things:
○ The forth paragraph in the introduction starts with “During the week of 24-28 October 2016...”. I suggest either avoiding that paragraph or formulating it differently. The reader should not be reading the meeting minutes.

Is the topic of the opinion article discussed accurately in the context of the current literature?
Yes

Are all factual statements correct and adequately supported by citations?
Yes

Are arguments sufficiently supported by evidence from the published literature?
Yes

Are the conclusions drawn balanced and justified on the basis of the presented arguments?
Partly

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Data management, multi-omics bioinformatics

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard, however I have significant reservations, as outlined above.
Thank you very much to Dr. Nahnsen for his review. We have responded to his comments below (reviewer comments in italics, our responses in plain text).

The article "Best practice data life cycle approaches for the life sciences", submitted by Griffin et al. reports opinions on how to best manage the growing complexity of scientific data in the life sciences.

The article touches on an extremely important topic that is currently very purely covered in the literature. In fact, data-driven approaches in the biosciences will strongly rely on professional concepts of data management. In brief, I recommend the indexing of the article, as we urgently need stronger awareness of this topic, upon the implementation of some (probably rather minor) changes to the article. The article nicely illustrates the needs in data life cycle management and also suggests best concepts to be followed by researchers.

Thank you.

The main content of the article has been compiled based on a workshop that was attended by the authors. At some statements the article reads like the minutes of this meeting; I suggest editing the corresponding paragraphs to avoid the impression of reading meeting minutes.

We have edited the Introduction (para 4), Integrating, Processing and Analysing Data section (para 4), the Sharing Data section (para 2) and the Conclusions section (para 1) to remove details of the events of the workshop, while still mentioning briefly in the Introduction (para 4) that this article arose from the material we presented and discussed in this workshop series.

I suggest the following issues to be fixed before indexing:

- **Figure 1**: This illustration is very important and can be used by many readers. I suggest to use figures wherever possible to replace the words such as “finding”, “integrating”, ...
  We experimented with adding icons to represent the life cycle stages, but found it too difficult to choose a single icon to summarise each complex stage. (For example: the ‘Storing Data’ stage text covers local data storage, primary archives, privacy and security considerations; one icon would necessarily omit or de-emphasise some of these.) Our attempts gave a misleading aura of simplicity, which we wanted to avoid, and so we prefer to retain the words in the figure, which map readily to the text of the article which contains the detail.

- **The reference to Figure 1 in the second paragraph** states that it illustrates a specific aim to the life sciences. I don't see which of these points should be specific to the life science, but would rather argue that these principles are rather generic and provides a cycle for business intelligence processes in general. It might also be a good location to reference the DAMA (Data management association international, dama.org) and specifically to the DAMA Body of Knowledge, which is one of the few references for data management and also data life cycle considerations. Further needed references should hint to the Global Alliance for Genomics and Health (ga4gh.org).
We agree that data life cycle principles can cut across disciplines and have mentioned other examples of published data lifecycle figures in the Introduction, para 2. As described in more detail in our response to Dr. Starlinger's review, we believe that our data lifecycle model is better suited to the way life science researchers work than more generic models. Specifically, we have included distinct steps for finding existing data and collecting new data (different from e.g. the USGS data lifecycle model) because in life science research these two steps typically have different limitations and considerations. We have included distinct ‘publish’ and ‘share’ steps (unlike the USGS, DataOne and Digital Curation Centre models) since publishing manuscripts and sharing data are highly distinct in the minds of most life science researchers due to the publication focus of life science research. Some models (e.g. the DataOne and Digital Curation Centre models) break down the ‘collecting data’ step (e.g. into collecting, quality-assuring and describing data) but we believe these stages are already rather well understood to be part of the data collection process in the life sciences and have kept them together.

We have been unable to find GA4GH publications dealing with the research data lifecycle but have now cited GA4GH documents in the Storing Data (para 1) and Sharing Data (para 1) sections. We have been unable to source a copy of DAMA International's Guide to the Data Management Body of Knowledge (https://technicspub.com/dmbok/) and so have not included this reference.

- Page 13: The paragraph on data sharing missing some discussion on authentication issues. I would like see some introduction and discussion to the OpenID concept. Especially for medical data there need to be appropriate mechanisms to trace users, concepts for data privacy and so on. As a best practice use case for these topics, the mechanism from ICGC could be introduced.

In the interests of keeping the paper a concise introduction to the concepts, we decided not to delve into too much detail around data privacy considerations, a topic that indeed warrants entire papers to itself. However we have now expanded the text in the Finding Data section (para 3), the Storing Data section (para 1) and the Sharing Data section (para 1) to make it clear to readers that for medical data, much extra planning and effort is required to deal with these considerations. We have also provided some explanation of why authentication might be necessary, links to some of the relevant technologies, and a reference (as suggested) to the practices of the ICGC.

- The following paragraph states: “A few workshop participants...“. Rephrase, no meeting minutes..

Done (Sharing Data section, para 2).

- I would have loved to see more use cases/examples for the individual best practices. E.g. for the data sharing the ICGC efforts could be described more thoroughly.

As the paper is aimed at individual researchers, we wanted to avoid an excessive focus on large-scale research consortium efforts, as the resources such projects have available for data management are likely to be far beyond what individual researchers can access.
However, we acknowledge these efforts often set a ‘best-practice’ standard and so we have now mentioned the Monarch Initiative (Integrating, Processing and Analysing Data section, para 1), the GA4GH (Sharing Data section, para 1) and the ICGC (cited in Finding Data section, para 2).

- The article would benefit for 2-3 additional figures. I guess it could be a nice figure to illustrate the concept of controlled vocabularies and/or ontologies. While this seems to be trivial for bioinformaticians/computer scientists, it is not that obvious what it means to non-computer scientists; inspiration for figures can also be obtained by the data sharing mechanisms for the Global alliance for Genomics and Health.

We have now included a second figure, an example flowchart (Figure 2) showing how the data life cycle might be used in practice and how downstream considerations influence choices made at each step. An extra figure illustrating CVs/ontologies we judged would make the paper somewhat unbalanced - we have referenced other articles (Thessen and Paterson 2001, Malone et al. 2016) that are good starting points for researchers keen to learn about this topic.

- The forth paragraph in the introduction starts with “During the week of 24-28 October 2016...”. I suggest either avoiding that paragraph or formulating it differently. The reader should not be reading the meeting minutes.

We have retained some reference to the origin of this article but rewritten the paragraph (Introduction, para 4) to avoid an appearance of meeting minutes.

Competing Interests: No competing interests were disclosed.
The article is well written and comfortable to read, and the concise presentation follows a clear structure. While to me as a biomedical data researcher, who may not strictly belong to the target audience, the article provided only little additional insight, I can well see how - as an entry point - the article provides valuable information to its target audience.

That said, I believe the article needs clarification and some extension in a few places:

- The list of authors is quite extensive. Please clarify the roles of the authors in conception/conduction/preparation of the manuscript.

- How exactly does the proposed data life cycle differ from related (cited) suggestions, and why? How is it ‘aimed at life science researchers specifically’? (Introduction)

- The tabular overviews of existing resources are a nice asset but they are, of course, not exhaustive. Please clarify how the selections of databases/registries, tools, ontologies etc were made for inclusion in the article - and possibly state where to find more complete lists of resources for the life sciences.

- The integrating step of the life cycle has no description in the article - even though this is a very intricate step that often has great influence when collecting data (e.g., the choice of ontologies to use for describing collected data and metadata will often depend on the ontologies used in re-used (found) data), and, even more, is at the core of making datasets interoperable, i.e., making them integratable with newly collected data.

- In the processing step, you make no mention of Scientific Workflows as a means of integrating, processing, and analyzing data. Your first reference (currently cited in a rather different context) would provide a very good hook for this thriving topic that is all about sharing, reproducibility, and reusability of data processing and analysis methods. On the same lines, containerized computing (e.g., Docker) is only very briefly mentioned. Even more than with data, using technologies such as these is crucial for ensuring reproducibility over longer periods of time (when software versions of dependencies have changed, web-services have become unavailable, and so forth).

- The section "What can the research community do to encourage best practice?" gives a rather remote, high level view that addresses several different institutional entities - except for the individual researcher within the target audience who actually has to follow the discussed best practices to enable the data life cycle.

Additionally, here are some suggestions for increasing the usefulness and potential impact of the article within the current target audience, and possibly beyond:

- Important interdependencies between the different steps of the life cycle could be mentioned. For instance, the choice of which ontologies to use for metadata and data in the collection step will necessarily be influenced by a) the ontologies used in the data found in public repositories and reused in the current experiment, b) the ontologies mandated by the repositories the data product is to be published in, and c) the ontologies required and used by the (third party, reused) software applied in the processing of the data. These interdependencies often not only put a limit to the choices available regarding the ontologies to be used but also raise a barrier when conversion and mapping between
different ontologies is necessary between steps in the life cycle.

○ The topic of data privacy is only very briefly touched but fundamental when it comes to sharing and publishing data. It may be out of scope of this article, but a slightly more thorough discussion of the issue would to its importance more justice, I feel.

○ An additional figure that maps the best practices enumerated in the text to the rather coarse life cycle shown in Figure 1 could prove highly instructive. Something like a ‘data life cycle best practices cheat sheet’ ;)

If you (the authors) have any questions regarding this review, please do not hesitate to contact me.

**Is the topic of the opinion article discussed accurately in the context of the current literature?**
Yes

**Are all factual statements correct and adequately supported by citations?**
Yes

**Are arguments sufficiently supported by evidence from the published literature?**
Yes

**Are the conclusions drawn balanced and justified on the basis of the presented arguments?**
Yes

**Competing Interests:** No competing interests were disclosed.

**Reviewer Expertise:** Biomedical knowledge management, systems architectures, clinical informatics

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard, however I have significant reservations, as outlined above.

Reader Comment 27 May 2018

Pip Griffin, The University of Melbourne, Australia

**Response to Review 2**

We thank Dr. Starlinger for his review and respond to his comments below (reviewer comments in italics, our responses in plain text).

*The article gives a brief overview of the data life cycle in the life sciences and offers an entry point for accessing relevant information about current approaches to increasing compliance with the FAIR data sharing principles at each step of this life cycle. It expressly targets “life science*
researchers wanting to improve their data management practice" and is labeled as an Opinion article.

The article is well written and comfortable to read, and the concise presentation follows a clear structure. While to me as a biomedical data researcher, who may not strictly belong to the target audience, the article provided only little additional insight, I can well see how - as an entry point - the article provides valuable information to its target audience.

Thank you.

That said, I believe the article needs clarification and some extension in a few places:

○ The list of authors is quite extensive. Please clarify the roles of the authors in conception/conduction/preparation of the manuscript.

The authorship roles are described in the ‘Author Details’ section using the F1000Research authorship classification scheme. To give a bit more detail, Maria Victoria Schneider and Philippa Griffin conceptualised the paper as a follow-up to the Data Life Cycle workshop series run by EMBL Australia Bioinformatics Resource (EMBL-ABR) in October 2016. Jyoti Khadake, Suzanna Lewis, Sandra Orchard, Andrew Pask, Bernard Pope, Ute Roessner, and Torsten Seemann were workshop faculty who presented sessions and led group discussions. Jeffrey Christiansen, Sonika Tyagi, Nathan Watson-Haigh, Saravanan Dayalan and Simon Gladman have Key Area Coordinator roles with EMBL-ABR. All other authors were workshop attendees who subsequently volunteered to contribute to the manuscript. Philippa Griffin drafted the manuscript with input and supervision from Maria Victoria Schneider. All authors then had the opportunity to edit and comment on the text, figures and tables (via a shared Google Doc) and did so through several revisions of the manuscript.

○ How exactly does the proposed data life cycle differ from related (cited) suggestions, and why? How is it ‘aimed at life science researchers specifically’? (Introduction)

This data life cycle is rather similar to others but we see it as having some important practical differences that make it more relevant to life science researchers, as follows:

The USGS data life cycle model does not include distinct steps for finding existing data and collecting new data (both are implied under ‘acquire’), whereas in the life sciences these two steps are performed differently, with different limitations and considerations and so we see the need for highlighting both. As Dr. Nahnsen (the other reviewer) has noted, the integration of existing and new data can also be very complex in the life sciences and so deserves a place in the data life cycle diagram (it does not occur in the USGS model). Finally, we have separated the ‘publish’ and ‘share’ steps since publishing manuscripts and sharing data are highly distinct in the minds of most life science researchers due to the publication-focussed way the world of life science research currently operates. Each has different actions relevant to good practice data management.

The DataOne data life cycle model has a heavier focus on data collection, with distinct steps for ‘collect’, ‘assure’, and ‘describe’. We would argue that data quality assurance is generally considered an intrinsic part of data collection in the life sciences and does not require its
own step. We also consider ‘description’ as part of the collection step as this should be done at the same time (or ideally planned beforehand), and we cover this in the article with the sections on metadata. This model also lacks the Publishing and Sharing steps (‘sharing’ is subsumed with ‘storing’ under ‘preserve’) which we believe are important, distinct considerations for life science researchers as mentioned above. The Digital Curation Centre data lifecycle model is similar to the DataOne model.

- The tabular overviews of existing resources are a nice asset but they are, of course, not exhaustive. Please clarify how the selections of databases/registries, tools, ontologies etc were made for inclusion in the article - and possibly state where to find more complete lists of resources for the life sciences.

These tables are intended to demonstrate the scope of the resources available and indeed are not exhaustive. The databases/registries, standards and ontologies presented were ‘crowd-sourced’ from the authors’ suggestions, in an attempt to present the most relevant options for resources used across the wide range of biology sub-domains this group of authors represents. We have now referenced FAIRsharing.org in the caption of the databases/registries and standards tables (Tables 1, 3 and 4), as this website contains more complete, maintained lists of resources.

- The integrating step of the life cycle has no description in the article - even though this is a very intricate step that often has great influence when collecting data (e.g., the choice of ontologies to use for describing collected data and metadata will often depend on the ontologies used in re-used (found) data), and, even more, is at the core of making datasets interoperable, i.e., making them integratable with newly collected data.

We have now changed the title of the Processing and Analysing Data section to Integrating, processing and analysing data to ensure this step is highlighted. The point about integration having great influence on the data collection and processing strategy is indeed important and we have now included a paragraph dealing with this explicitly (Integrating, Processing and Analysing Data section, para 1).

- In the processing step, you make no mention of Scientific Workflows as a means of integrating, processing, and analyzing data. Your first reference (currently cited in a rather different context) would provide a very good hook for this thriving topic that is all about sharing, reproducibility, and reusability of data processing and analysis methods. On the same lines, containerized computing (e.g., Docker) is only very briefly mentioned. Even more than with data, using technologies such as these is crucial for ensuring reproducibility over longer periods of time (when software versions of dependencies have changed, web-services have become unavailable, and so forth).

We agree this is an active and important area of development in the research reproducibility field. We have now expanded the Integrating, Processing and Analysing Data section (para 2) to include mention of scientific workflows, workflow repositories and containerized computing.

- The section "What can the research community do to encourage best practice?" gives a
rather remote, high level view that addresses several different institutional entities - except for the individual researcher within the target audience who actually has to follow the discussed best practices to enable the data life cycle.

Thanks for pointing this out - we have now added three recommendations for individual researchers at the start of this section as follows:

1. Researchers reusing any data should openly acknowledge this fact and fully cite the dataset, including unique identifiers.

2. Researchers should endeavour to improve their own data management practices in line with best practice in their subdomain - even incremental improvement is better than none!

3. Researchers should provide feedback to their local institution, data repositories and bodies responsible for community resources (data formats, controlled vocabularies etc.) where they identify roadblocks to good data management.

Additionally, here are some suggestions for increasing the usefulness and potential impact of the article within the current target audience, and possibly beyond:

- Important interdependencies between the different steps of the life cycle could be mentioned. For instance, the choice of which ontologies to use for metadata and data in the collection step will necessarily be influenced by a) the ontologies used in the data found in public repositories and reused in the current experiment, b) the ontologies mandated by the repositories the data product is to be published in, and c) the ontologies required and used by the (third party, reused) software applied in the processing of the data. These interdependencies often not only put a limit to the choices available regarding the ontologies to be used but also raise a barrier when conversion and mapping between different ontologies is necessary between steps in the life cycle.

At the risk of making the paper too long, we agree it is important to point out the complexities and interdependencies that can be involved in good data management practice (this actually helps explain why it is implemented rather haphazardly at present). We have now included a flow-chart (Figure 2) as a guide to how a researcher might actually use a data life cycle approach. It is still rather high-level but shows how downstream requirements influence choices made at each stage of a research project.

- The topic of data privacy is only very briefly touched but fundamental when it comes to sharing and publishing data. It may be out of scope of this article, but a slightly more thorough discussion of the issue would to its importance more justice, I feel.

We agree that data privacy is fundamental for research involving human data and have now expanded the text in the Finding Data section (para 3), the Storing Data section (para 1) and the Sharing Data section (para 1) to make it clear to readers that for human data, much extra planning and effort is typically required to deal with these considerations.

- An additional figure that maps the best practices enumerated in the text to the rather
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