















Towards standard practices for sharing computer code and programs in neuroscience

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Background

2 Many areas of neuroscience are now critically dependent on computational tools to help
understand the large volumes of data being created. Furthermore, computer models are
4 increasingly being used to help predict and understand the function of the nervous sys-
tem. Many of these computations are complex and usually cannot be concisely reported
6 in the methods section of a scientific article. In a few areas there are widely used software
packages for analysis (e.g., SPM, FSL, AFNI, FreeSurfer, Civet in neuroimaging) or sim-
8 ulation (e.g. NEURON, NEST, Brian). However, we often write new computer programs
to solve specific problems in the course of our research. Some of these programs may be
10 relatively small scripts that help analyze all of our data, and these rarely get described
in papers. As authors, how best can we maximize the chances that other scientists can
12 reproduce our computations, find errors, or reuse our methods on their data? Is our
research reproducible¹?

14 To date, the sharing of computer programs underlying neuroscience research has
been the exception (see below for some examples), rather than the rule. However, there
16 are many potential benefits to sharing these programs, including increased understand-
ing and reuse of your work. Furthermore, open source programs can be scrutinized and
18 improved, whereas the functioning of closed source programs remains forever unclear².
Funding agencies, research institutes and publishers are all gradually developing policies
20 to reduce the withholding of computer programs relating to research³. The Nature family
of journals has published opinion pieces in favor of sharing whatever code is available,
22 in whatever form^{4,5}. Since October 2014, all Nature journals require papers to include a
statement declaring *whether* the programs underlying central results in a paper are avail-
24 able. In April 2015 *Nature Biotechnology* offered recommendations for providing code
with papers and began asking referees to give feedback on their ability to test code that
26 accompanies submitted manuscripts⁶. In July 2015 F1000Research stated that “Software
papers describing non-open software, code and/or web tools will be rejected” ([http://](http://f1000research.com/channels/f1000-faculty-reviews/for-authors/article-guidelines/software-tool-articles)
28 [f1000research.com/channels/f1000-faculty-reviews/for-authors/article-guidelines/](http://f1000research.com/channels/f1000-faculty-reviews/for-authors/article-guidelines/software-tool-articles)
[software-tool-articles](http://f1000research.com/channels/f1000-faculty-reviews/for-authors/article-guidelines/software-tool-articles)). Also in July 2015, BioMed Central introduced a minimum
30 standards of reporting checklist for BMC Neuroscience and several other journals, re-
quiring submissions to include a code availability statement and for code to be cited
32 using a DOI or similar unique identifier⁷. We believe that all journals should adopt poli-
cies that highly encourage, or even mandate, the sharing of software relating to journal
34 publications as this is the only practical way to check the validity of the work.

What should be shared?

36 It may not be obvious what to share, especially for complex projects with many collabora-
tors. As advocated by Claerbout and Donoho, for computational sciences the scholarship
38 is not the article; the “scholarship is the complete software [...]”^{8,9}. So, ideally, we should
share all code and data needed to allow others to reproduce our work, but this may not

40 be possible or practical. However, it is expected that the key parts of the work should be
shared, e.g. implementations of novel algorithms or analyses. At a minimum, we suggest
42 following the recommendation of submission of work to ModelDB¹⁰, i.e. to share enough
code, data and documentation to allow at least one key figure from your manuscript to
44 be reproduced. However, by adopting appropriate software tools, as mentioned in the
next section, it is now relatively straightforward to share the materials required to regen-
46 erate *all* figures and tables. Code that already exists, is well tested and documented, and
is reused in the analysis should be cited. Ideally, all other code should be communicated,
48 including code that performs simple preprocessing or statistical tests, or code that deals
with local computing issues such as hardware and software configurations. While this
50 code may not be reusable, it will help others understand how analyses are performed,
find potential mistakes, and aid reproducibility. Finally, if the work is computationally
52 intensive and requires a long time to run (e.g. many weeks), one may prefer to provide a
small “toy” example to demonstrate the code.

54 By getting into the habit of sharing as much as possible, not only do we help others
who wish to reproduce our work (which is a basic tenet of the scientific method), we
56 will be helping other members of our laboratory, or even ourselves in the future. By
sharing our code publicly, we are more likely to write higher-quality code¹¹, and we
58 will know where to find it after we have moved on from the project¹², rather than the
code disappearing on a colleague’s laptop when they leave your group, or suffer some
60 misfortune¹³. We also will be part of a community and benefit from the code shared by
others, thus reducing software development time for ourselves and others.

62 **Simple steps to help you share code**

Once you have decided *what* to share, here are some simple guidelines for *how* to share the
64 work. Ideally, these principles should be followed throughout the lifetime of the research
project, not just at the end when we wish to publish our results. Guidelines similar to
66 these have been proposed in many areas of science^{14–16}, suggesting that they are part of
norms that are emerging across disciplines. In the ‘further reading’ section below, we list
68 some specific proposals from other fields that expand on the guidelines we suggest here.

Version control Use a version control system (such as Git) to develop the code¹⁷. The
70 version control repository can then be easily and freely shared with others using
sites such as <http://github.com>¹⁸ or <https://bitbucket.org>. These sites allow
72 you fine control over private versus public access to your code. This means that you
can keep your code repository private during its development, and then publicly
74 share the repository at a later stage e.g. at the time of publication, although we
recommend opening the code from the start of the project. It also makes it easy for
76 others to contribute to your code, and to adapt it for their own uses.

Persistent URLs Generate stable URLs (such as a DOI) for key versions of your software.

78 Unique identifiers are a key element in demonstrating the integrity and repro-
ducibility of research¹⁹, and allow referencing of the exact version of your code used
80 to produce figures. DOIs can be obtained freely and routinely with sites such as
<http://zenodo.org> and <http://figshare.com>. If your work includes computer
82 models of neural systems, you may wish to consider depositing these models in es-
tablished repositories such as ModelDB¹⁰, Open Source Brain²⁰ or NITRC²¹. Some
84 of these sites allow for private sharing of repositories with anonymous peer review-
ers. Journal articles that include a persistent URL to code deposited in a trusted
86 repository meet the requirements of level two of the ‘analytic methods (code) trans-
parency’ standard of the TOP guidelines¹⁴.

88 **License** Choose a suitable license for your code to assert how you wish others to reuse
your code. For example, to maximize reuse, you may wish to use a permissive
90 license such as MIT or BSD²². Licenses are also important to protect you from others
misusing your code. Visit <http://choosealicense.com/> to get a simple overview
92 of which license to choose, or [http://www.software.ac.uk/resources/guides/
adopting-open-source-licence](http://www.software.ac.uk/resources/guides/adopting-open-source-licence) for a detailed guide.

94 **Etiquette** When working with code written by others, observe Daniel Kahneman’s ‘re-
producibility etiquette’²³ and have a discussion with the authors of the code to give
96 them a chance to fix bugs or respond to issues you have identified before you make
any public statements. Cite their code in an appropriate fashion.

98 **Documentation** Contrary to popular expectations, you do not need to write extensive
documentation or a user’s guide for the code to still be useful to others⁴. However,
100 it is worth providing a minimal README file to describe what the code does, and
how to run it. For example, you should provide instructions on how to regenerate
102 key results, or a particular figure from a paper. Literate programming methods,
where code and narrative text are interwoven in the same document, make docu-
104 mentation semi-automatic and can save a lot of time when preparing code to ac-
company a publication^{24,25}. However, these methods admittedly take more time to
106 write in the first instance, and you should be prepared to rewrite documentation
when rewriting code. In any cases, well-documented code allows for easier re-use
108 and checking.

Tools Consider using modern, widely used software tools that can help with making
110 your computational research reproducible. Many of these tools have already been
used in neuroscience and serve as good examples to follow, for example Org mode²⁶,
112 IPython/Jupyter²⁷ and Knitr²⁸. Virtualization environments, such as VirtualBox
appliances and Docker containers, can also be used to encapsulate or preserve all
114 of the computational environment so that other users can run your code without
having to install numerous dependencies²⁹.

116 **Case studies** In addition to the examples listed above in Tools^{26–28}, there are many prior
examples to follow when sharing your code. For example, some prominent exam-
118 ples of reproducible research in computational neuroscience include Vogels et al.³⁰
and Waskom et al.³¹; see <https://github.com/WagnerLabPapers> for details. The
120 ModelDB repository contains over 1000 computational models deposited with in-
structions for reproducing key figures to papers e.g. [https://senselab.med.yale.
122 edu/ModelDB/showModel.cshtml?model=93321](https://senselab.med.yale.edu/ModelDB/showModel.cshtml?model=93321) for a model of activity-dependent
conductances³².

124 **Data** Any experimental data collected alongside the software should also be released or
made available. For small datasets, this could be stored alongside the software,
126 although it may be preferable to store experimental data separately in an appro-
priate repository. Both PLOS and Scientific Data maintain useful lists of subject-
128 specific and general repositories for data storage, see [http://journals.plos.org/
plosbiology/s/data-availability#loc-recommended-repositories](http://journals.plos.org/plosbiology/s/data-availability#loc-recommended-repositories) and [http:
130 //www.nature.com/sdata/data-policies/repositories](http://www.nature.com/sdata/data-policies/repositories).

Standards Use of (community) standards, where appropriate, should be encouraged, in
132 particular use of non-proprietary formats to enable long-term accessibility. In com-
putational neuroscience for example, PyNN³³ and NeuroML³⁴ are widely used for-
134 mats for making models more accessible and portable across multiple simulators.
Neuroimaging data and results can be organized using BIDS³⁵.

136 **Tests** Testing the code has long been recognized as a critical step in the software industry
but the practice is not widely adopted yet by researchers. We recommend includ-
138 ing test suites that demonstrate the code is producing the correct results³⁶. These
tests can be at a low level (testing each individual function, called unit testing) or
140 at a higher level (e.g. testing that the program yields correct answers on simu-
lated data)³⁷. With public data available, it is often straightforward to have a test
142 verifying that published results can be recomputed. Linking tests to continuous in-
tegration services (such as Travis CI, <https://travis-ci.org>) allows these tests to
144 be automatically run each time a change is made to the code, ensuring failing tests
are immediately flagged and can be dealt with quickly.

146 **User support** Although some people are eager to provide support for their code after
it has been published, others may feel that they do not want to be burdened by
148 e.g. feature requests. One simple suggestion to avoid this is to establish a user
community for the code³⁸. This could be as simple as creating a mailing list or
150 asking for issues to be posted on a github repository.

Further reading (note to editor: please make this a box feature)

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Online communities discussing code sharing (note to editor: please make this a box feature)

StackExchange and related projects StackExchange is a network of free and highly active question-and-answer websites. Two members of the network are relevant to questions of code sharing: <http://stackoverflow.com/> which is dedicated to questions about programming in any language in any context, and <http://academia.stackexchange.com/questions/tagged/reproducible-research> which is focused questions relating to reproducible research in academic context. A related project is <https://neurostars.org/> which is a similar free public Q&A website focused on neuroinformatics questions, and with many questions on software packages, etc.

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Scientists for Reproducible Research This is an international multi-disciplinary email list that discusses a wide range of issues relating to code sharing: <https://groups.google.com/forum/#!forum/reproducible-research>

GitHub GitHub is an online repository for computer code and programs that has a large community of researchers that develop and share their code openly on the site. GitHub is the largest and most active code sharing site (others include BitBucket and GitLab) and has convenient tools for facilitating efficient collaborative coding^{39,40}. If you are using an open source program you may find a community of users and developers active on GitHub, where you can ask questions and report problems.

Closing remarks

154 Changing the behaviors of neuroscientists so that they make their code more available
will likely be resisted by those who do not see the community benefits as outweighing
156 the personal costs of the time and effort required to share code⁴¹. The community ben-
efits, in our view, are obvious and substantial: we can demonstrate more robustly and
158 transparently the reliability of our results, we can more easily adapt methods developed
by others to our data, and the impact of our work increases as others can similarly reuse
160 our methods on their data. Thus, we will endeavor to lead by example, and follow all
these practices as part of our future work in all scientific publications. Even if the code
162 we produce today will not run ten years from now, it will still be a more precise and
complete expression of our analysis than the text of the methods section in our paper.

164 However, exhortations such as this article are only a small part of making code shar-
ing a normal part of doing neuroscience; many other activities are important. All re-
166 searchers should be trained in sound coding principles; such training is provided by
organizations such as Software Carpentry³⁷ or Data Carpentry and through national neu-
168 roinformatics initiatives, e.g. <http://python.g-node.org>. Furthermore, we should re-
quest code and data when reviewing, and submit to and review for journals that support

170 code sharing. Grant proposals should be checked for mentions of code availability, and
we should encourage efforts toward openness in hiring, promotion, and reference let-
172 ters⁴². Funding agencies and editors should also consider mandating code sharing by
default. This combination of efforts on a variety of fronts will increase the visibility of
174 research accompanied by open source code, and demonstrate to others in the discipline
that code sharing is a desirable activity that helps move the field forward.

176 We believe that the sociological barriers to code sharing are harder to overcome than
the technical ones. Currently, academic success is strongly linked to publications and
178 there is little recognition for producing and sharing code. Code may also be seen as
providing a private competitive advantage to researchers. We challenge this view and
180 propose that code be regarded as part of the research products and part of the publi-
cation in which should be shared by default, and that there should be an obligation to
182 share code for those conducting publicly funded research. We hope the code availabil-
ity review (*CITE JOURNAL EDITORIAL HERE*) will help establish such sharing as the
184 norm. Moreover, we are advocating for code sharing as part of a broader culture change
embracing transparency, reproducibility, and re-usability of research products.

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