Checklist Strategies to Improve the Reproducibility of Deep Learning Experiments with an Illustration

Ali Ben Abbess, Leonardo Meneguzzi, Pedro Pizzigatti Corrêa, David Mouillot, Romain David, Gérard Subsol, Danton Ferreira Vellenich, Rodolphe Devillers, Shelley Stall, Nicolas Mouquet, et al.

Reproducibility checklist: pre-screen your Deep Learning experiment prior to your submission or publication!

The description of the dataset
☐ Are there relevant statistics?
☐ Is the dataset open access?
☐ Are there clear details of training / validation / test splits?
☐ Is there an explanation of any data that was excluded, and all pre-processing steps?
☐ Is there a link to a downloadable version of the dataset or simulation environment?
☐ For new data collected, is there a complete description of the data collection process?
FAIR sub-principles (Findability, Accessibility, Interoperability, Reusability)
☐ Are (Meta)data assigned with a globally unique and persistent identifier? (F1)
☐ Are data described with rich metadata? (F2)
☐ Are (Meta)data retrievable by their identifier using a standardized communications protocol? (A1)
☐ Do (Meta)data include qualified references to other (meta)data? (I3)
☐ Are Metadata richly described with a plurality of accurate and relevant attributes? (R1)
☐ Are (Meta)data associated with detailed provenance? (R1.2)
Reported experimental results and theoretical claim
☐ Is there a clear measure or statistics used to report results?
☐ A description of results with central tendency & variation
☐ The average runtime for each result, or estimated energy cost
☐ Is there a clear statement of the claim?
☐ Is there a complete proof of the claim?

The description of the DL architecture and hyper-parameter optimisation process
☐ Is there a clear description of the mathematical and/or DL model?
☐ Does the paper use a Cross-Validation strategy?
☐ Is there a clear explanation of assumptions?
☐ Is there an analysis of the complexity of any algorithm?
☐ Does the paper use an Optimization procedure? Which one?
☐ Were the Hyper-Parameters handcrafted (selected manually)?
☐ Does the paper clearly mention the use of Learning rate?
☐ Does the paper clearly mention the use of Batch size?
☐ Does the paper use Dropout regularization?
☐ Are there a clear description of hyper-parameters?
☐ Is there an exact number of training and evaluation runs?
The infrastructure and implementation
☐ Does the paper detail the infrastructure adequately?
☐ Which framework was used?
The shared code
☐ Is the shared code Open source?
☐ Is there a specification of dependencies?
☐ Is there a training code?
☐ Is there an evaluation code?
☐ Is there a (Pre-)trained model(s)?
☐ Is there a README file?

Table 1: Compiled **Checklist** from Machine Learning checklist Pineau, (2020) [2], the recommendations from Renard et al, 2020 [3], and the FAIR sub-principles (following Hartley & Olsson 2020) [4] aiming to pre-screening Deep Learning experiments to achieve Reproducibility.

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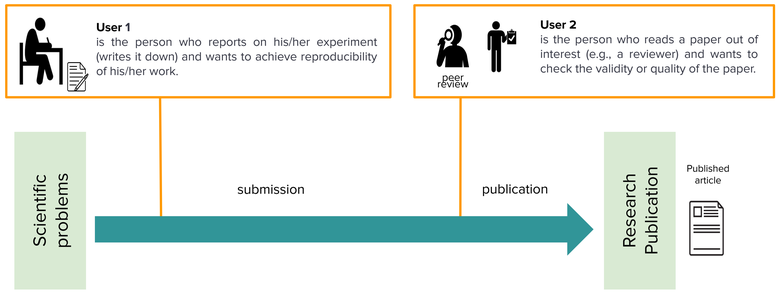
Authors: A. Ben Abbes, J. Machicao, L. Meneguzzi, P.L.P. Corrêa, A. Specht, R. David, G. Subsol, D. Vellenich, R. Devillers, S. Stall, N. Mouquet, M. Chaumont, L. Berti-Equille, D. Mouillot
Contact: pedro.correa@usp.br **Website**: https://parsecproject.org/ **twitter**: @PARSEC_News

Reproducibility and Replicability (R&R):

The challenges of Reproducibility and Replicability have become a focus of attention in order to promote **open and accessible research**. Therefore, efforts have been made to develop good practices for R&R in the area of computer science. Nevertheless, **Deep Learning** (DL) based experiments **remain difficult to reproduce** by others due to the complexity of these techniques. In addition, several challenges concern the use of massive and heterogeneous data that contribute to the complexity of this R&R.

Checklist:

We compiled a checklist (Table 1) with the most relevant items for Reproducibility to improve DL experiments.
This checklist is useful for: an **author reporting on an experiment**, and/or a **reviewer seeking to qualify the scientific contributions** of the work.
This table is based on state-of-the-art guidelines from Pineau's Machine Learning checklist [2], the recommendations from Renard's [3], and the FAIR sub-principles (Hartley & Olsson) [4]. Besides that, we organized these criterias according to a DL workflow.



How to use?

We report a review of the reproducibility of three publications for Poverty estimation using DL and Remote sensing imagery. For each experiment, we identified the methods and workflows used, if the experiments were not fully reproducible. Although the three use cases were proposed for a specific task (poverty estimation), we believe that the evaluation methods could be applied to more general Deep Learning tasks, where difficulties might include (a) a lack of dataset specificity (and the metadata related with it), (b) inadequate description of the DL methodology, (c) the implementation methodology, and the infrastructure used. We also feel that these recommendations can be extended to other domains such as medical, climatic, biodiversity, industrial, military, etc.

References:

[1] Peng, R. D. (2011), Reproducible Research in Computing Science. Science 334, 1226–1227.

[2] Pineau, J. (2020b). The Machine Learning reproducibility checklist (v2.0, Apr.7 2020). www.cs.mcgill.ca/~jpineau/ReproducibilityChecklist-v2.0.pdf

[3] Renard, F., Guedria, S., Palma, N.D., & Vuillerme, N. (2020). Variability and reproducibility in deep learning for medical image segmentation. Scientific Reports 10(1), 1–16.

[4] Hartley, M., & Olsson, T. S. G. (2020), dtoolAI: Reproducibility for Deep Learning. Patterns 1(5), 100073.

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Author affiliations : Ali Ben Abbes (FRB-CESAB, Montpellier, FR) https://orcid.org/0000-0001-5714-7562; Jeaneth Machicao (University of São Paulo, BR) https://orcid.org/0000-0002-1202-0194; Leonardo Meneguzzi (University of São Paulo, BR) https://orcid.org/0000-0002-4845-6758; Pedro Pizzigatti Corrêa (University of São Paulo, BR) https://orcid.org/0000-0002-8743-4244; Alison Specht (The University of Queensland, AU) https://orcid.org/0000-0002-2623-0854; Romain David (ERINHA (European Research Infrastructure on Highly Pathogenic Agents) AISBL, FR) https://orcid.org/0000-0003-4073-7456; Gérard Subsol (Research-Team ICAR, LIRMM, CNRS, Univ. Montpellier, FR) https://orcid.org/0000-0002-7461-4932; Danton Ferreira Vellenich (University of São Paulo, BR), https://orcid.org/0000-0002-3223-6996; Shelley Stall, American Geophysical Union, USA) https://orcid.org/0000-0003-2926-8353; Nicolas Mouquet (FRB-CESAB, Montpellier, FR), https://orcid.org/0000-0003-1840-6984; Marc Chaumont (LIRMM, CNRS) https://orcid.org/0000-0002-4095-4410; Laure Berti-Equille (Espace-Dev (IRD-UM-UG-UR-UA-UNC), Montpellier, FR) https://orcid.org/0000-0002-8046-0570; David Mouillot (MARBEC, University of Montpellier) https://orcid.org/0000-0003-0402-2605.