# FAIR for non-data objects: some context

- FAIR Principles, at a high level, are intended to apply to all research objects; both those used in research and those that are research outputs
- Text in principles often includes "(Meta)data …"
  - Shorthand for "metadata and data …"
- Principles applied via dataset creators and repositories, collectively responsible for creating, annotating, indexing, preserving, sharing the datasets and their metadata
  - Assumes separate and sequential creator/publisher (repository) roles
- What about non-data objects?
  - While they can often be stored as data, they are not just data
- While high level goals (F, A, I, R) are mostly the same, the details and how they are implemented depend on
  - How objects are created and used
  - How/where the objects are stored and shared
  - How/where metadata is stored and indexed
- Work needed to define, then implement, then adopt principles

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# Need for FAIR for non-data objects

- FAIR Principles, are intended to apply to all digital objects (Wilkinson et al. 2016)

**FAIR Practice Task Force EOSC, "Six Recommendations for Implementation of FAIR Practice," 2020:**

***Recommendation 5**:*

*Recognise that FAIR guidelines will require **translation for other digital objects** and support such efforts.*

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# FAIR and ML Models

- As previously stated, original FAIR principles
  - Claim to apply to "scholarly digital research objects"
  - But actually focus on metadata and data
- FAIR for Research Software work and FAIR Workflows focusing on how to translate/interpret the principles for research software & workflows
- What about machine learning (ML) models?
  - Are they data?
    - E.g., a set of parameters and options for a particular framework
  - Are they software?
    - E.g., an executable object that takes input and provides output
  - Are they a combination of data+ software + workflows?
  - Are they something else?

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# How does FAIR apply?

- Large elements of FAIR for data are dependent on archival repositories (e.g. Zenodo, re3data.org)
  - Hold data and/or metadata, provide search and access capabilities
- Software is different, since it typically isn't shared via archival repositories but instead via social coding platform (e.g., GitHub) and package management systems (e.g. PyPI, CRAN)
- What about ML models?
  - Searched and shared via repositories?
  - Searched and shared via executable platforms?
  - Searched and shared via something else? (e.g., DLHub, OpenML, …)
- Models and training data are linked - should they be shared together?

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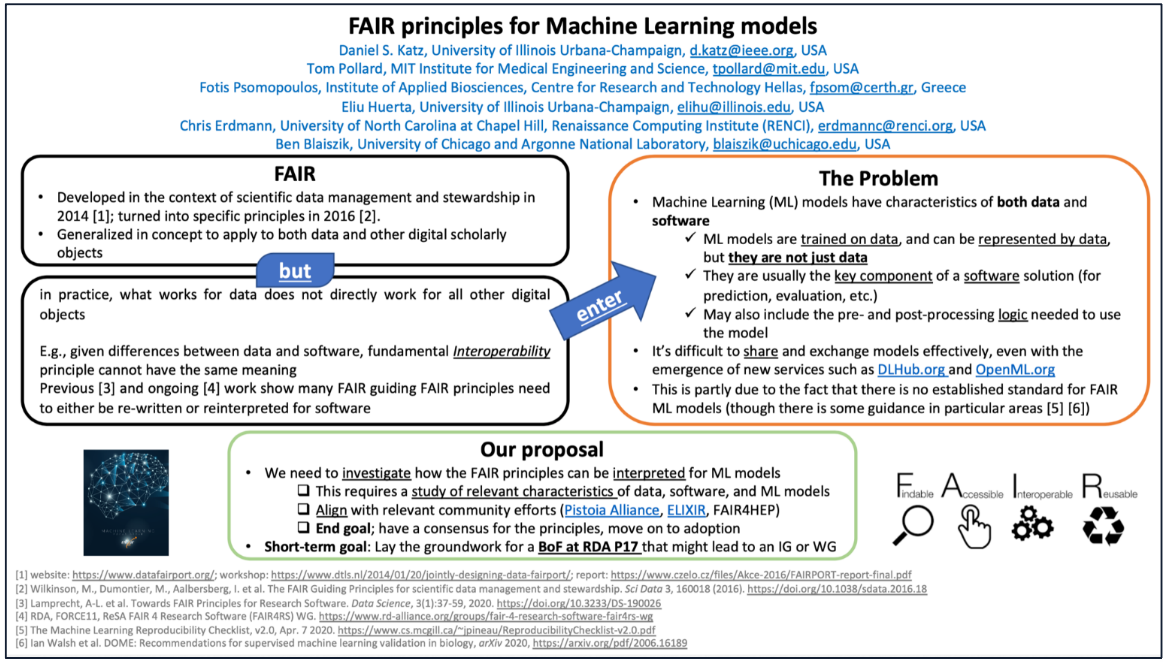
# Work to-date and going forward

- Poster at RDA VP16 (Nov 2020):
- BoF at RDA VP17 (Apr 2021):
- FAIR for Machine Learning Models (Jun 2021), FAIR Festival
- 1st Community call (Jul 2021)
- DaMaLOS talk (24 Oct 2021)
- BoF at RDA VP18 (4 & 9 Nov 2021)
- BoF at SC21 (18 Nov 2021)
- BoF at RDA P19 (23 Jun 2022)

- Discussing a possible new interest group
- Discussing a potential white paper on FAIR 4 ML



## FAIR principles for Machine Learning models

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### FAIR

- Developed in the context of scientific data management and stewardship in 2014 [1]; turned into specific principles in 2016 [2].
- Generalized in concept to apply to both data and other digital scholarly objects

**but**

in practice, what works for data does not directly work for all other digital objects

E.g., given differences between data and software, fundamental *Interoperability* principle cannot have the same meaning
Previous [3] and ongoing [4] work show many FAIR guiding FAIR principles need to either be re-written or reinterpreted for software

**enter**

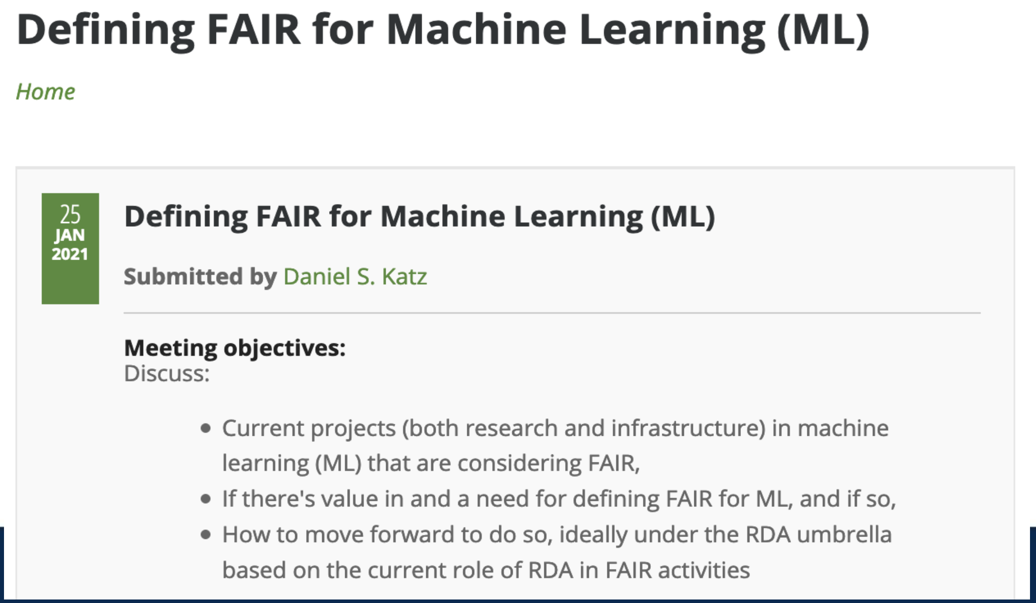
### The Problem

- Machine Learning (ML) models have characteristics of **both data** and **software**
  - ✓ ML models are trained on data, and can be represented by data, but **they are not just data**
  - ✓ They are usually the key component of a software solution (for prediction, evaluation, etc.)
  - ✓ May also include the pre- and post-processing logic needed to use the model
- It's difficult to share and exchange models effectively, even with the emergence of new services such as DLHub.org and OpenML.org
- This is partly due to the fact that there is no established standard for FAIR ML models (though there is some guidance in particular areas [5] [6])

### Our proposal

- We need to investigate how the FAIR principles can be interpreted for ML models
  - ❑ This requires a study of relevant characteristics of data, software, and ML models
  - ❑ Align with relevant community efforts (Pistoia Alliance, ELIXIR, FAIR4HEP)
  - ❑ **End goal**; have a consensus for the principles, move on to adoption
- **Short-term goal**: Lay the groundwork for a **BoF at RDA P17** that might lead to an IG or WG

[1] website: https://www.datafairport.org/; workshop: https://www.dtls.nl/2014/01/20/jointly-designing-data-fairport/; report: https://www.czelo.cz/files/Akce-2016/FAIRPORT-report-final.pdf
[2] Wilkinson, M., Dumontier, M., Aalbersberg, I. et al. The FAIR Guiding Principles for scientific data management and stewardship. *Sci Data* 3, 160018 (2016). https://doi.org/10.1038/sdata.2016.18
[3] Lamprecht, A-L. et al. Towards FAIR Principles for Research Software. *Data Science*, 3(1):37-59, 2020. https://doi.org/10.3233/DS-190026
[4] RDA, FORCE11, ReSA FAIR 4 Research Software (FAIR4RS) WG. https://www.rd-alliance.org/groups/fair-4-research-software-fair4rs-wg
[5] The Machine Learning Reproducibility Checklist, v2.0, Apr. 7 2020. https://www.cs.mcgill.ca/~jpineau/ReproducibilityChecklist-v2.0.pdf
[6] Ian Walsh et al. DOME: Recommendations for supervised machine learning validation in biology, *arXiv* 2020, https://arxiv.org/pdf/2006.16189



## Defining FAIR for Machine Learning (ML)

*Home*

25
JAN
2021

### Defining FAIR for Machine Learning (ML)

**Submitted by** Daniel S. Katz

**Meeting objectives:**
Discuss:

- Current projects (both research and infrastructure) in machine learning (ML) that are considering FAIR,
- If there's value in and a need for defining FAIR for ML, and if so,
- How to move forward to do so, ideally under the RDA umbrella based on the current role of RDA in FAIR activities

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# Relevant projects & stakeholders

- Platforms
  - DLHub - Find, share, publish, and run machine learning models and discover training data for science
  - Kipoi - API & repository of ready-to-use trained models for genomics
  - OpenML - Build open source tools to discover (and share) open data, draw them into machine learning environments, build models, analyse results, get advice on better models
- Communities
  - Pistoia Alliance - a global, not-for-profit members' organization working to lower barriers to innovation in life science and healthcare R&D through pre-competitive collaboration
  - ELIXIR - An intergovernmental organisation that brings together life science resources (including databases, software tools, training materials, cloud storage and supercomputers) from across Europe
  - CLAIRE - Confederation of Laboratories for Artificial Intelligence Research in Europe
- Projects
  - FAIR4HEP - Using high-energy physics (HEP) as the science driver, developing a FAIR framework to advance understanding of AI, applying AI techniques, and exploring approaches to AI
  - HPC-FAIR - Providing a generic HPC data management framework to make both training data and AI models of scientific applications FAIR, focusing on the domain of program analyses/optimizations using AI/ML
- Others? Please contact Dan

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