A FAIR Approach to Data and Machine Learning Using *funcX*

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The Growing Importance of ML and Data in the Sciences

Data and ML are becoming key drivers of scientific progress



How do we use these models?

For a given study:

- •Where is the code?
- •Where are the trained models?
- •Where are the training data?
- •How can I reproduce these results?

Without all of these pieces, progress is drastically slowed

Need models and data to be FAIR:

Findable Accessible Interoperable Reusable



Location of many ML models after a paper is finished

DLHub for FAIR Models



DLHub Example

• What if I want to evaluate a model from a paper?

SCIENTIFIC REPORTS

Article | OPEN | Published: 08 November 2018

Real-time coherent diffraction inversion using deep generative networks

Mathew J. Cherukara 🛰, Youssef S. G. Nashed & Ross J. Harder

Scientific Reports 8, Article number: 16520 (2018) | Download Citation ↓

DLHub supplies both computational environment and resources



Run

structure_model = "npruyne_globusid/cherukara_structure"
phase_model = "npruyne_globusid/cherukara_phase"

```
# Load testing data
n_test = 10
intensity_threshold = 0.2
X = ft_test[0:n_test].tolist()
```

```
# Call to DLHub to get predictions
intensities = np.asarray(dl.run(structure_model, X))
phases = np.asarray(dl.run(phase_model, X))*2*np.pi-np.pi
```

Plot and Explore



DLHub Containers with funcX

Container



we then register the container and the function dlhub_run() with funcX

dlhub_run(event)

from home_run import create_servable
with open("dlhub.json") as fp:
 shim = create_servable(json.load(fp))

dlhub.json contains all servable-specific info

DLHub Use Case Examples

X-Ray Science

- Predict structure and phase of a material given coherent diffraction intensity
- Data available from Github



Energy Storage

- Predict molecular energies with G4MP2 accuracy at B3LYP cost
- Data available in MDF

Machine Learning Prediction of Accurate Atomization Energies of Organic Molecules from Low-Fidelity Quantum Chemical Calculations

Logan Ward^{1,2}, Ben Blaiszik^{1,3}, Ian Foster^{1,2,3}, Rajeev S. Assary^{4,5}, Badri Narayanan^{5,6}, Larry Curtiss^{4,5}



Tomography

- Enhance tomographic scans and remove noise using generative adversarial model
- Example data available on Petrel

TomoGAN: Low-Dose X-Ray Tomography with Generative Adversarial Networks

Zhengchun Liu, Tekin Bicer, Rajkumar Kettimuthu, Doga Gursoy, Francesco De Carlo, Ian Foster







Foundry Concept







(Dane Morgan, Paul Voyles, Michael Ferris, Marcus Schwarting, Aristana Scourtas, KJ Schmidt, Ben Blaiszik)

Thank You!



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Integrative Materials and Design



MICHIGAN

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Backup Slides

What are FAIR Data Principles?

• <u>F</u>indable

Set of principles to help make data as useful as possible to the community

- <u>A</u>ccessible
- Interoperable
- <u>R</u>eusable



https://www.force11.org/group/fairgroup/fairprinciples

What is the state of FAIR data and ML in materials science?

FAIR Data Principles

<u>F</u>indable

- Data have an identifier
- Data are registered in a searchable resource

<u>A</u>ccesible

- Data accessible via identifier
- Data retrievable by open protocols

FAIR Data Principles

- Data leverage formalized shared vocabularies
- Vocabularies themselves follow FAIR principles

<u>R</u>eusable

- Clear licensing
- Descriptive metadata is sufficient to promote reuse



The Materials Data Facility (MDF)



- Connect: Extract domain-relevant metadata / transform the data
- Publish: Built to handle big data (many TB, millions of files), provides persistent identifier for data, distributed storage enabled
- Discover: Programmatic search index to aggregate and retrieve data across hundreds of indexed data sources

https://www.materialsdatafacility.org



The Materials Data Facility

DATA AND LEARNING HUB FOR SCIENCE (DLHUB)

- <u>Collect</u>, <u>publish</u>, <u>categorize</u> models and pre/post processing code
- <u>Operate</u> models as a service to simplify sharing, consumption, and access

16

- Identify models with unique and persistent identifiers (e.g., DOI)
- <u>Implement</u> versioning, search, access controls etc.

Goal: Deliver FAIR for ML













DLHub – A Data and Learning Hub for Science



Search index for **DOI** for model Ability to run models discovery on distributed Unique endpoint for compute resources Python tooling each model ARGONNE LEADERSHIP

COMPUTING FACILITY

Building on Globus PaaS

Globus Platform: Automation

- Authentication
- User groups
- Data staging and movement
- Automation capabilities
- Search

