



FARR:

FAIR in ML, AI Readiness, & Reproducibility Research Coordination Network



BRDI

April 20, 2023

SDSC
SAN DIEGO SUPERCOMPUTER CENTER

NC STATE
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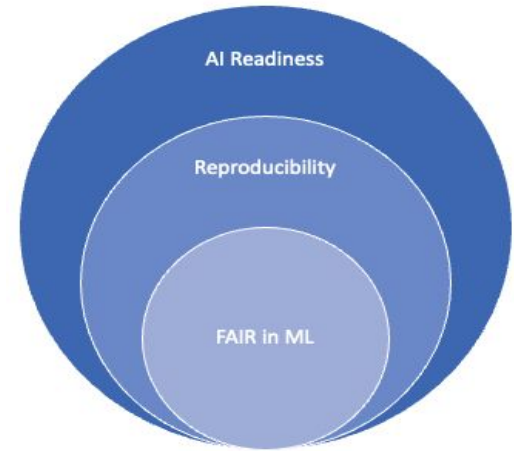
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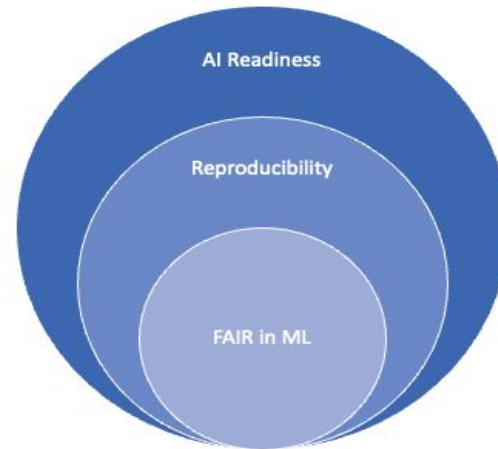
This work is supported through the NSF award #2226453.

Motivation

- If 80% of time spent with data is wrangling, can FAIR principles increase efficiency of people and machines?
- What does it mean for a repository or an organization to be AI ready?
 - What roles can repositories play in AI readiness?
- What are community practices in AI reproducibility?
 - What are the gaps in current knowledge?

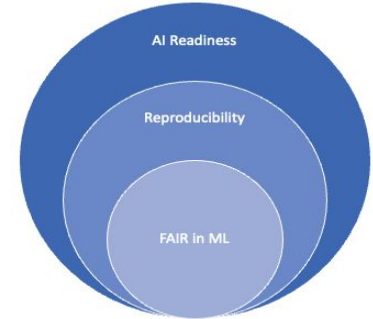


AI Readiness



Literature Review of 'AI Readiness'

- Term used in computer science, healthcare, business, systems engineering
- Granularity varies: country, organizations/companies, data
- Definition examples
 - **Quantity and quality of AI-related research** in a country (Vuong)
 - **Preparedness** of organizations **to implement change** involving applications and **technology related to AI** (Najdawi)
 - Organization's abilities to **deploy and use AI** in ways *that add value* to the organization (Holmström's AI Readiness framework)
 - AI readiness process comprises a set of **strategic actions to be performed prior to AI adoption** (Issa)
 - **Data that can support AI solutions** should be known, understood, available, fit for purpose, secure (McKinsey's 5 Steps to AI ready data)



AI Readiness Frameworks

Table 2: Extended TOE framework for AI-Readiness at Business

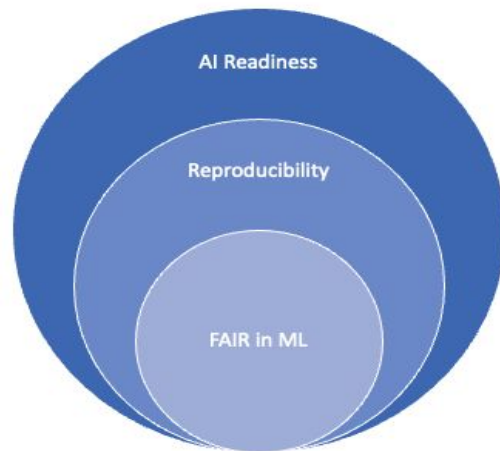
Readiness Dimensions	Main Categories	Sub-Categories
Technology Readiness	Relative advantage	
	Compatibility	Business process*, Business case*
Organizational Readiness	Culture *	Top management support, change Management*, Innovative Culture*
	Organizational Size	
	Resources	Budget*, employees*, data* (availability, protection and quality)
	Organizational Structure*	
Environmental Readiness	Competitive pressure	
	Government regulatory issues	Employees'council, General Data Protection Regulation (GDPR)*
	Industry requirements *	
	Customer readiness *	



Najdawi, Anas. (2020). Assessing AI Readiness Across Organizations: The Case of UAE. 1-5.

<https://doi.org/10.1109/ICCCNT49239.2020.9225386> ; Holmström, J. (2022). From AI to digital transformation: The AI readiness framework. *Business Horizons*, 65(3), 329–339. <https://doi.org/10.1016/j.bushor.2021.03.006>

AI Reproducibility



AI Results Can Vary (Software Bug)

Processing Unit:Software Environment	0	1	2	3	4
NVIDIA A40:tensorflow_22.03	0.86584	0.86584	0.86584	0.86584	0.86584
NVIDIA A100-40GB:tensorflow_22.03	0.86580	0.86580	0.86580	0.86580	0.86580
Tesla V100-16GB:tensorflow_22.03	0.85203	0.85203	0.85203	0.85203	0.85203
NVIDIA A40:tensorflow_22.06	0.86584	0.86584	0.86584	0.86584	0.86584
NVIDIA A100-40GB:tensorflow_22.06	0.86580	0.86580	0.86580	0.86580	0.86580
Tesla V100-16GB:tensorflow_22.06	0.85203	0.85203	0.85203	0.85203	0.85203
NVIDIA A40:tensorflow_2.8.0-gpu	0.86571	0.86555	0.85680	0.85927	0.86147
NVIDIA A100-40GB:tensorflow_2.8.0-gpu	0.86511	0.84516	0.86360	0.85895	0.86479
Tesla V100-32GB:tensorflow_2.8.0-gpu	0.85983	0.78835	0.85764	0.86031	0.86908
NVIDIA A40:tensorflow_2.9.1-gpu	0.83631	0.86287	0.83891	0.85724	0.85276
NVIDIA A100-40GB:tensorflow_2.9.1-gpu	0.85979	0.86619	0.83156	0.86412	0.84564
Tesla V100-16GB:tensorflow_2.9.1-gpu	0.84447	0.85320	0.85996	0.86511	0.86779
NVIDIA A40:tensorflow_2.9.1-gpu-cuda11.3-cudnn8.2	0.86184	0.86184	0.86184	0.86184	0.86184
NVIDIA A100-40GB:tensorflow_2.9.1-gpu-cuda11.3-cudnn8.2	0.84631	0.84631	0.84631	0.84631	0.84631

Slide source: Kevin Coakley (SDSC/NTNU)

Tolerance for Erroneous Conclusions: High

Image classification

Find the four-leafed clover →

0187683105	0.8626000285148621	0.8573200106620789	0.8610799908638000	0.864920020
9915313721	0.8525599837303162	0.8678799867630005	0.8515599966049194	0.867999970
0276374817	0.8572800159454346	0.8664399981498718	0.8625199794769287	0.862119972
9826049805	0.8642799854278564	0.8643199801445007	0.8637199997901917	0.862919986
9908638000	0.8507199883460999	0.8378000259399414	0.8429200053215027	0.857400000
0108718872	0.8612400293350220	0.8637199997901917	0.8675600290298462	0.867839992
9786567688	0.8600000143051147	0.8575999736785889	0.8620799779891968	0.835240006
0290298462	0.8675600290298462	0.8675600290298462	0.8675600290298462	0.867560029
0204086304	0.8561199903488159	0.8648800253868103	0.8633199930191040	0.862119972
0290298462	0.8675600290298462	0.8675600290298462	0.8675600290298462	0.867560029
9830055237	0.8628799915313721	0.8389199972152710	0.8572400212287903	0.852760016
9857330322	0.8658800125122070	0.8632799983024597	0.8652399778366089	0.843840003
0012779236	0.8557199835777283	0.8619599938392639	0.8493199944496155	0.809239983
0214385986	0.8543199896812439	0.8555999994277954	0.8573200106620789	0.85979998
9811172485	0.8661999702453613	0.8315600156784058	0.8641200065612793	0.845640003
9716758728	0.8642399907112122	0.8579599857330322	0.8552399873733521	0.862680017
9885559082	0.8166800141334534	0.8648800253868103	0.8613200187683105	0.858680009
0199508667	0.8500400185585022	0.8637599945068359	0.8516399860382080	0.861039996
9983024597	0.8689600229263306	0.8511599898338318	0.8640800118446350	0.85535997



Tolerance for Erroneous Conclusions: Low

Running nnUNet with Medical Imaging

Input

Ground truth

A40/22933937
L1 DICE: 0.8502202643171806
L2 DICE: 0.8470282559272491

A100/22933910
L1 DICE: 0.8468335787923417
L2 DICE: 0.837012987012987

A100/22972197
L1 DICE: 0.8483500185391175
L2 DICE: 0.8377942599161561

A100/22972221
L1 DICE: 0.8694706308919506
L2 DICE: 0.8575197889182058

A100/22996510
L1 DICE: 0.8437150317045878
L2 DICE: 0.8390655418559377

**What amount of error
is tolerable?**

**Need to quantify
the variance**

FARR Goals and Activities

We welcome individual researchers, institutions/organizations, CI providers, repositories/facilities, and networks of facilities in Computer Science, Geosciences, and the 'Research Data' Community. FARR provides a neutral and novel meeting place for bridging multiple networks.

- Building communities to
 - promote better practices for AI
 - harness community efforts
 - improve efficiency and reproducibility
 - stimulate and enhance new research
- Activities will include
 - workshops
 - assessing community needs
 - fostering new collaborations (proposals)
 - setting research agendas
 - community-led reports

Incorporating EarthCube's sustainability lessons from the beginning.

FARR Team



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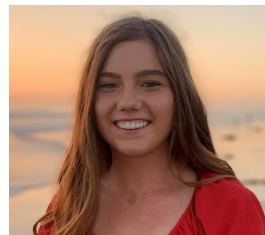
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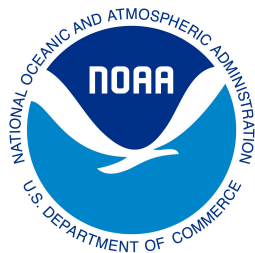
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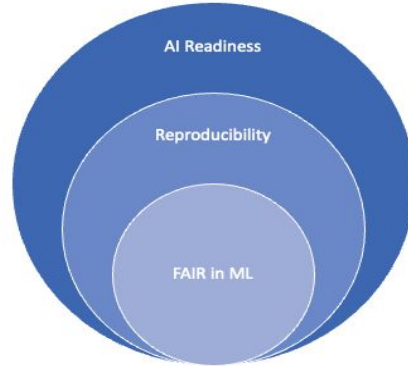
FARR Partners



Early Signals

- (AI) Reproducibility is complex and resource intensive
 - Must prioritize key aspects to document
 - Lack of awareness of issue
 - Excellent library personnel who want to help
 - Papers >3 years old difficult to reproduce
 - *Even if containers are provided*
 - Suggests shifting priorities for curation teams
- AI Readiness
 - Definition evolving within communities
 - The other FAIR - Fully AI Ready
 - How do I get there?
 - Are we there yet?
 - How will I know when I'm FAIR?
- Listening Tour
 - Need for onramps:
 - 'Where do I start with AI?'
 - How do I choose a GPU?

Thank You



For more info, contact us at community@farr-rcn.org
To join our mailing list, visit <http://farr-rcn.org>