The pre-registration experiment An alternative publication model for ML research NeurIPS 2021

Opening remarks 13th December 2021 Up-to-date schedule and details at http://preregister.science/



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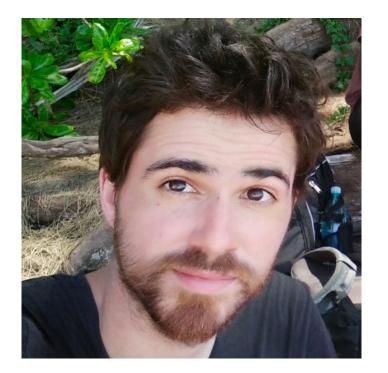
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A huge thank you to our reviewers!

Organisers



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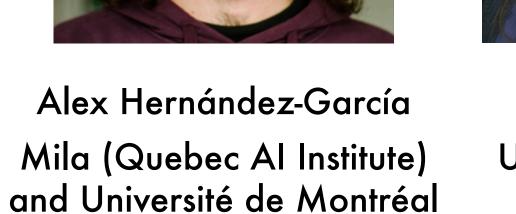


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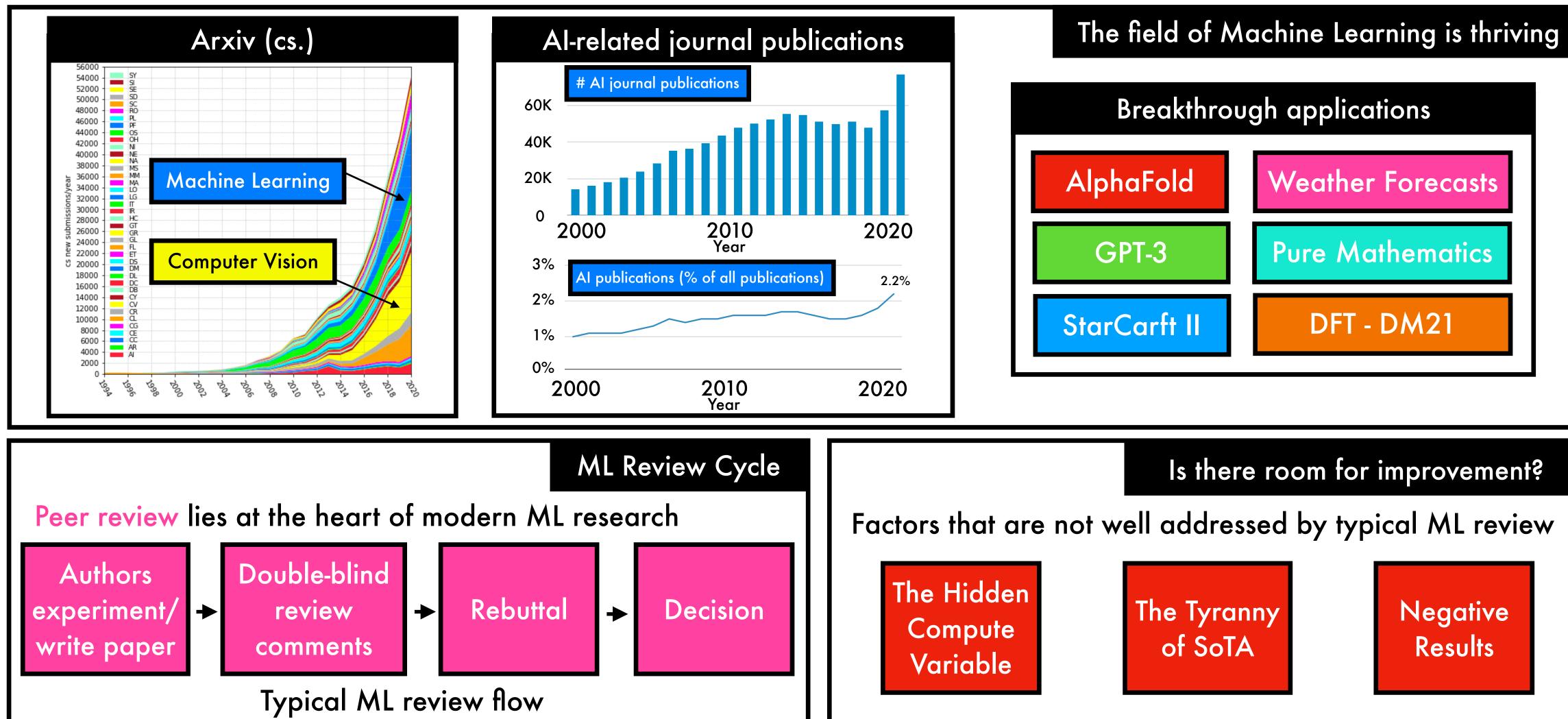
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Motivation for the workshop



References

arxiv stats figures <u>https://github.com/arXiv/arxiv-docs/tree/develop/help/stats/2020_by_area</u> Journal figures: <u>https://aiindex.stanford.edu/wp-content/uploads/2021/03/2021-Al-Index-Report-Chapter-1.pdf</u> Jumper et al. "Highly accurate protein structure prediction with AlphaFold." *Nature* (2021) Brown et al. "Language Models are Few-Shot Learners." *NeurIPS 2020*



The Hidden Compute Variable

Same

In the typical ML review process reviewers (and paper readers) do not know how many experiments were run. Issue if significant disparity in computing resources available to different researchers evaluating on same benchmarks.

Blue Researcher (3 GPUs)

	Arch a	Arch b	Arch c
Run 1	72.6	73.8	76.6
Run 2	70.4	71.5	76.7
Run 3	78.9	73.8	73.7
Mean	73.1	70.2	72.7
Std	4.4	1.3	1.7

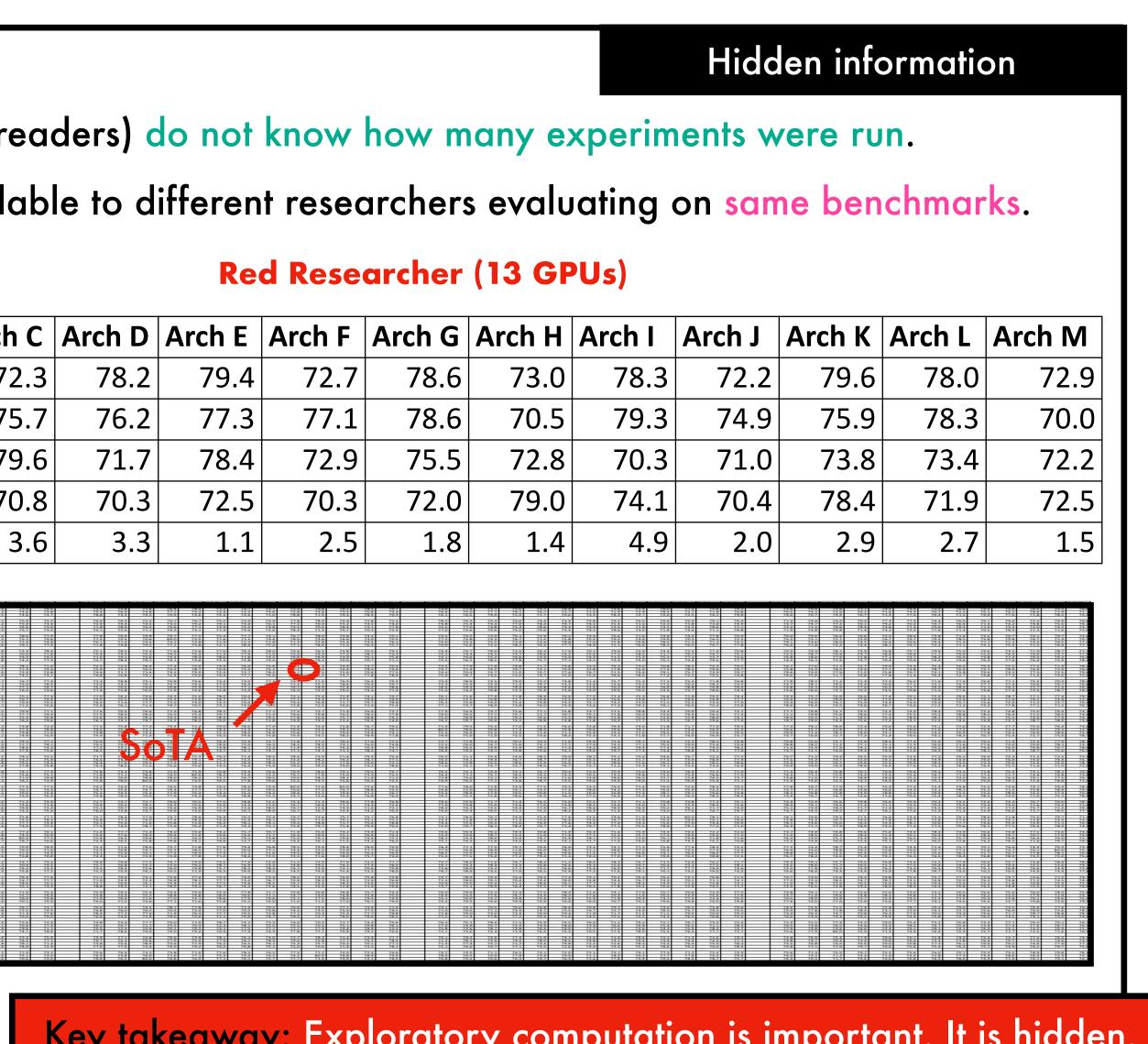
Arch A	Arch B	Arch C	Arch D	Arch E	Arch F	Arch G	Arch H	Arch I	Arch J	Arch K	Arch L	Arch M
79.4	71.3	72.3	78.2	79.4	72.7	78.6	73.0	78.3	72.2	79.6	78.0	72.9
75.6	76.6	75.7	76.2	77.3	77.1	78.6	70.5	79.3	74.9	75.9	78.3	70.0
74.7	77.0	79.6	71.7	78.4	72.9	75.5	72.8	70.3	71.0	73.8	73.4	72.2
79.2	72.3	70.8	70.3	72.5	70.3	72.0	79.0	74.1	70.4	78.4	71.9	72.5
2.5	3.2	3.6	3.3	1.1	2.5	1.8	1.4	4.9	2.0	2.9	2.7	1.5

What the reviewer sees

	Arch a	Arch A
Run 1	72.6	79.4
Run 2	70.4	75.6
Run 3	78.9	74.7
Mean	73.1	79.2
Std	4.4	2.5

Table 1: Importantly, our Arch A outperforms their Arch a by a wide margin, with a lower standard deviation across runs

75.9	72.5	71.3 71.9 74.8	75.8 78.4 74.6	71.5 74.5 78.0	74.6	74.4 75.0 77.9	78.3	71.5 71.5 76.3	75.5 75.1 74.9	
72.5	70.7		74.6				38.3	76.3		
77.1 79.5 71.8	37.6 78.4 70.0	72.3 80.0 79.9	39.6 33.0 33.4	78.4 73.1 71.1	39.3 37.1 32.6	73.1 75.6 78.0	80.0 79.8 72.7	36.3	72.9 72.9 76.0	3
31.6	35.5	39.9	32.4	37.1	72.6	78.0	72.7	71.1	76.0	
39.3 38.0	73.3 70.4	75.3 70.8	31.4	70.3 77.6	75.3 71.0	79.1 78.3	71.3	38.4	76.3	
								33.4		
33.9	31.5	72.6	35.6	36.4	78.1	39.6	33.3	37.0	35.1	-
74.0	73.3	35.4	78.8	76.0	71.6	71.0	70.8	37.0	72.5	
37.8	73.4	79.5	39.3	71.5	75.2	72.6	72.0	75.3	72.4	
34.6	39.0	38.5	30.3		31.0	37.1	32.2	76.0	31.5	
78.3	71.1 71.0	70.1	71.1 77.8	74.3 78.8	74.4	73.0	72.3	39.5	37.4	
73.7	70.5	72.3	78.3	74.8 73.7	79.3	75.8 74.9	73.3	71.1 72.3	73.6 79.0	
71.6	74.4 75.0	76.6	71.6	23.3	77.1 75.9	72.5	78.0	37.3	27.5	
71.6	35.0	30.4	71.6	25.8	25.9	76.3	75.1 70.3		78.7 70.4	
37.5	35.3	37.9	36.3	36.9	79.3	31.0 31.9	75.1	34.5	71.6	
74.6 78.6	70.8	30.5	37.8 39.0	33.5 39.3	72.0 70.8	76.9 79.7	78.0	78.3	79.3 73.4	3
78.6 78.6 70.8	71.1 79.3 75.4	31.3 32.5 36.5	39.0 32.3 34.3	39.3 31.0 30.4	70.8 70.9 72.1	39.3 35.1 80.0	78.5 73.9 79.1	39.0 38.1 38.5	73.4 75.5 74.5	3
71.8	78.6	72.0 79.3	29.3 73.9	76.4	72.5	74.4	35.1 70.3	70.6	76.5	
70.5	71.3	73.8	78.9	27.4	32.1 35.4	74.0	73.0	79.4	35.4	
73.8	78.7		75.4	74.2			77.7	75.5	78.4	
75.1	24.6	77.1 72.3 70.5	70.1	710.3	77.3	71.9 72.6 75.9	78.1	73.0	73.9	
71.D 76.D	71.4 70.5	70.5	28.4	23.5 25.3	38.4		78.9	72.6	75.6	1
23.9	78.9	72.6	72.4	23.2	25.5	25.8	71.4	76-3	29.4	
76.6	79.8	72.6	75.8	23.6 23.5	76.3	76.1	77.8	35.6	35.6 34.0	
72.1	70.1	3.95	30.4	71.1	78.1	39.9	37.6	34.0	76.7	
71.9 75.9 77.0	71.0 72.6 79.4	73.1 74.3 74.7	77.5 73.0 73.3	76.7	70.3 72.6 72.1	70.1 75.3 77.3	73.4 74.0 79.0	79.3 76.1 70.3	74.8 76.5 75.2	
77.D 70.6	29.4	74.7	22.4	79.1 77.1	72.1 76.3	27.4 74.8	79.0 71.6	70.3	25.3	
72.3	79.3	78.6	37.4	39.3	79.5	71.9	77.6	74.3	72.5	_
71.8	39.1	27.3 76.4	78.0	73.2	79.1 79.8	75.6	76.0	35.9 39.0	76.0	
35.6	33.1	39.1	34.3	71.3	71.7	70.9	76.8	71.4	71.8	1
33.3	73.5 77.4 72.7 77.9	76.3 2723 75.3	74.6 75.6 75.3	70.8	79.0	70.3	36.4	75.7	36.9	
76.1	31.4	772	75.3	70.8 77.0 71.4	73.4 75.5 70.9	70.3 77.4 75.7	36.4 37.3 70.4		70.8	
35.3		33.6	72.0	78.8		31.6	70.6	35.6	31.1	
71.8 80.0	76.6	78.1	37.3	79.6 72.4	30.4	70.3	71.7	76.3	38.9	
30.4	79.3	75.3 77.1	79.6 70.5	76.3	75.7	78.3	76.7	35.9	76.0	
70.1 74.3	77.5 76.0	714 373	73.5 75.1	35.1 35.4	21.1 76.5	310.4 318.1	72.6	79.4 78.9	714	
74.3 79.3 79.4	36.0 37.4 39.3	373	75.1 74.7 79.7	75.4 76.8 75.8	76.5 71.5 72.3	78.1 77.9 70.3	72.6	38.5 78.5 78.6	76.3	
							76.7			
76.3	72.2	25.3 76.0	76.0	74.9	37.2	36.3	74.5 75.5	38.3	37.0	
76.0	70.8	71.1	35.0	31.4	35.3	74.3	76.8	70.7	70.6	
11.2			27.3	70.8				78.6	73.3	
71.3	70.8	37.1	74.7	74.5	71.1 76.3	76.9	71.3	75.6	75.6	
74.0	78.6	35.0 35.4	25.1 72.5	31.9	24.3	71.6	79.6 79.6	78.8	76.7	
21.1	71.1	70.1	70.3	78.2	73.5	71.7	76.4	71.5	79.2	
79.5	37.6 78.0	74.8 75.4 76.5	76.3 72.9 79.7	25.5 22.3	71.1 75.4 76.1	37.6 36.3 72.6	78.4	78.7	78.3	
39.3	23.3			35.8			35.5	37.4		
74.1 76.7	78.5	72.5	76.9 74.8	79.D 75.D	77.£ 76.£	70.9	76.4	76.9 76.4	78.6	
73.9	22.1	73.6 72.7 78.1	78.4	76.9	72.7	24.1 28.1	78.0	22.5	70.7	
78.4	79.3	25.7	74.9	34.0	71.0	79.9	39.3	78.5	79.1	
78.4 79.4 76.5	73.5	33.3	73.3	36.3	71.0	75.9 75.9 77.2	34.3	78.8	70.9	1
76.5	72.1	75.5	75.3	21.2	27.6	77.2	79.1	74.0	36.9 36.9 37.4	
78.8	73.5	71.2	37.4	78.3	72.6	70.1	72.3	70.9	26.3	
72.3	74.3	76.1 77.8	38.0	76.1	73.0	75.3	39.D 38.9	37.0 70.3	74.6	
36.3	37.8	36.0	36.5	36.1	31.4	78.7	72.3	37.0	34.3	
71.8	74.3	75.6 73.2 75.9	73.1 76.4	76.0	79.1	72.4	71.4	78.9	73.3	
76.3	72.4	75.9	36.4	36.3	78.3	39.6	28.4	39.5	77.3	
31.1	71.8	76.6	72.6	30.3	32.2	39.9	35.9	79.9	71.5	
39.4	79.6 72.6 76.8	76.5 70.6 78.9	32.0	73.1 79.2	77.5	79.7	71.3 73.6 77.3 71.9	78.8 73.5 78.7	73.1 71.6 77.9	
79.9	76.8	78.9	80.0	75.6	73.6	73.8	77.3	78.7	77.6	
70.9	73.0	76.4	74.6	73.0	77.8	71.6	76.9	75.0	79.0	
71.6	713	71.3	25.7	78.8	72.0	72.3	78.6	76.5	74.5	



Key takeaway: Exploratory computation is important. It is hidden.

The Tyranny of SOTA

Common experimental benchmark datasets have been incredibly valuable for our field.

- They allow direct, controlled comparisons of methods
- Drive community progress towards important research questions
- Highlight scenarios where existing methods fail

By practical necessity, benchmarks can often only provide an simplified (imperfect) model for a phenomenon of interest.

Misalignment: Over-reliance on benchmarks can produce make achieving state-of-the-art (SOTA) more important than advancing the collective knowledge of the community about underlying phenomena that we care about.

Misallocation: They can lead to inefficient resource allocation by trapping the community in local minima (neural networks....)

Degradation: Statistical power heavily affected by disparities in exploratory compute; weakens over time.





Benchmarks: benefits

Benchmarks: risks

Key takeaway: Benchmarks are very important, but they have challenges





Negative Results

Well-motivated, well-executed experiments can provide inconclusive and/or negative results.

No incentive to invest time in preparing such results for publication, since they would be highly unlikely to be accepted.

But these results can convey useful information for the community:

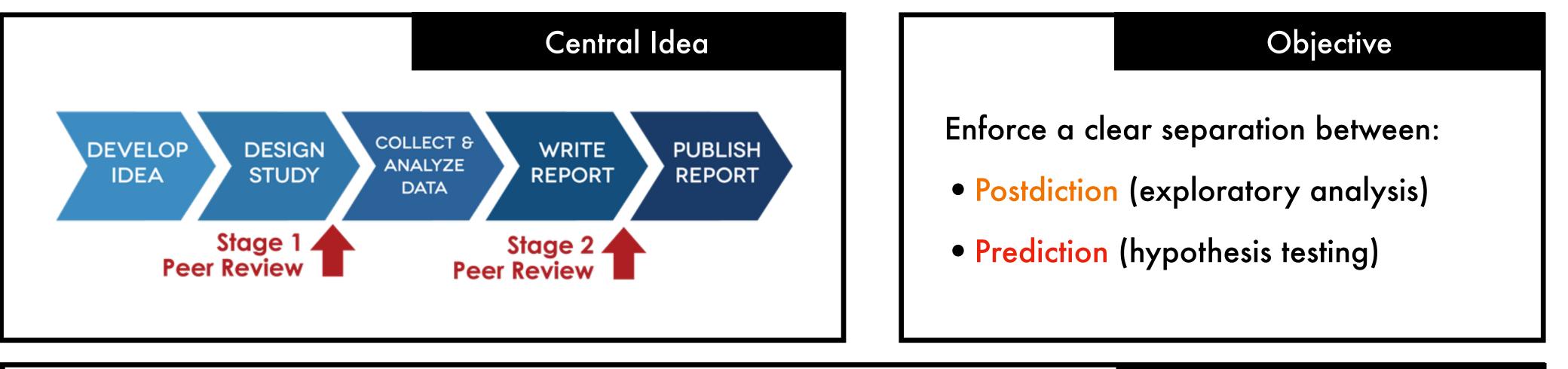
- Avoid duplication (wasted resources)
- Provide insight (particularly if detailed studies are conducted to understand the cause of the negative result)

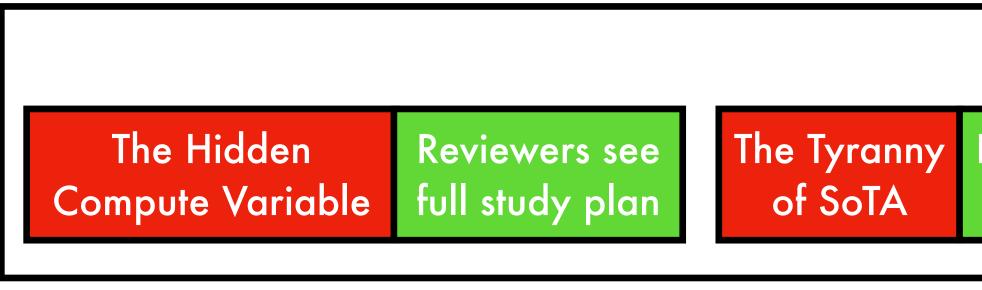
Incentives for Negative Results

Key takeaway: No incentive for negative results in typical ML review process



Pre-registration Protocol





Not suitable for all types of paper (highly exploratory work, for example)

Not a defence against dishonesty

Reference Figure credit: https://www.cos.io/initiatives/registered-reports

	Benefits				
Reviewer cannot accept/ reject based on SoTA	Negative Results	Review before results are known			
orv work, for example)		Limitations			

Pre-registration - workshop

Objective: conduct a full pre-registration review process

- Submit a pre-registration proposal (4-5 pages)
- Two rounds of review (including rebuttal)

10 accepted proposals (from 22 submissions) will be presented here today.

This is the second NeurIPS pre-registration workshop for Machine Learning. Following the workshop last year, accepted results papers were published at a special edition of PMLR.

We will hear from the authors of of several papers from last year who published results papers in the workshop today!

Authors of accepted proposals will be invited to submit their results to another special issue of PMLR.

Workshop protocol

What about results?



Sessions

- Invited talks will be followed by live Q&A
- Spotlights will be followed by live shared Q&A
 - to answer questions
- The **poster session** will take place on **GatherTown.** The link can be found at <u>http://preregister.science/</u>
- The **final session** is a live **open discussion** everyone is invited to participate.

• If you are an author in the session, please join the zoom link (at https://neurips.cc/virtual/2021/workshop/21885)



Asking Questions

Questions can be asked on RocketChat - we will read them aloud to the speakers

best to write your questions before the end of the talk).

recording before it is shared.

- Important note: There is a delay of 60 seconds between the zoom session and the NeurIPS streaming webpage (so it's
- If you wish to ask a question in person, join the zoom link and raise your hand (so we can promote you as panelist).
- Recording notice: we are recording the workshop. Please let us know afterwards if you would like to be removed from the



Workshop schedule (GMT)

Mon 12:00 p.m 12:10 p.m.	Opening remarks (Talk)	
Mon 12:10 p.m 12:40 p.m.	Invited Talk - Sarahanne Field (Talk) SlidesLive Video »	Sarahanne Field
Mon 12:40 p.m 1:00 p.m.	PCA Retargeting: Encoding Linear Shape Models as Convolutional Mesh Autoencoders - Eimear O'Sullivan (Talk)	
Mon 1:00 p.m 1:20 p.m.	Spotlights 1 (5 x 3 minutes) (Short videos)	
Mon 1:20 p.m 1:40 p.m.	Unsupervised Resource Allocation with Graph Neural Networks - Miles Cranmer (Talk)	
Mon 1:40 p.m 2:10 p.m.	Break	
Mon 2:10 p.m 2:40 p.m.	Invited Talk - Dima Damen (Talk)	Dima Damen
Mon 2:40 p.m 3:10 p.m.	Invited Talk - Hugo Larochelle (Talk)	Hugo Larochelle
Mon 3:10 p.m 3:30 p.m.	Spotlights 2 (5 x 3 minutes) (Short videos)	
Mon 3:30 p.m 4:30 p.m.	Poster Session (Virtual posters) link »	
Mon 4:30 p.m 5:00 p.m.	Break	
Mon 5:00 p.m 5:30 p.m.	Invited Talk - Paul Smaldino (Talk)	Paul Smaldino
Mon 5:30 p.m 5:50 p.m.	Confronting Domain Shift in Trained Neural Networks - Carianne Martinez (Talk)	
Mon 5:50 p.m 6:05 p.m.	Discussion Panel - 2020 authors' experience (Discussion Panel)	
Mon 6:05 p.m 7:05 p.m.	Open Discussion	
Mon 7:05 p.m 7:10 p.m.	Closing Remarks	

We are here

Schedule can be found on NeurIPS workshop page (<u>https://neurips.cc/</u> <u>virtual/2021/workshop/21885</u>)

and the workshop webpage http://preregister.science/



Thank you!

Up-to-date schedule and details at http://preregister.science/

