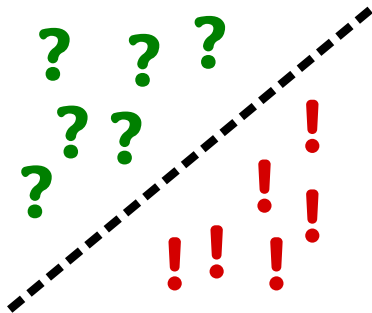


# Metascience for ML

Preaching to the Choir

June 20, 2025



Jan van Gemert



Assoc. prof; head Computer Vision lab @ PRB

Two main research themes:

- ① Fundamental empirical understanding-based deep learning research; (to)
- ② Find & evaluate powerful yet flexible physical priors for data-efficient visual recognition AI.

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## **I signed up because...**

I want to share my vision and learn from others how they do ML research.

## **Metascience for Machine Learning is...**

A method for doing research.

## **I would like to contribute to metascience for ML by...**

My own incomplete work-in-progress methodology :).

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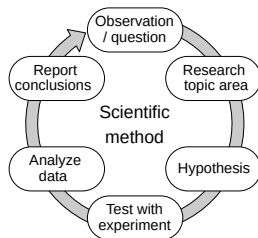
## **I would like to contribute to metascience for ML by...**

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Mine is not “*The Way*”; it’s “*A Way*”.

# The scientific method<sup>[1]</sup> in times of deep learning

Deep learning powers AI; yet as a scientific field has growing pains<sup>[2,3,4]</sup>



- Improvement-driven (large compute/data);
- Trial and error (graduate student descent)
- Opportunistic (career driven);
- Reviewer damage (Benchmark fetish; Mathiness);
- Confusing speculation with explanation
- Not identifying the reasons for empirical gains.

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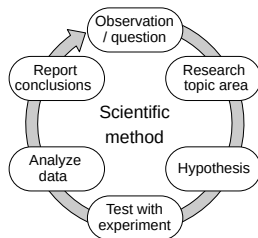
[2]: Lipton et al. "Troubling Trends in Machine Learning Scholarship", 2018.

[3]: Sculley, David, et al. "Winner's curse? On pace, progress, and empirical rigor." 2018.

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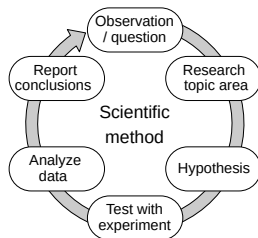
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  - Neural Scaling Laws;
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  - ML is like physics/neuroscience;
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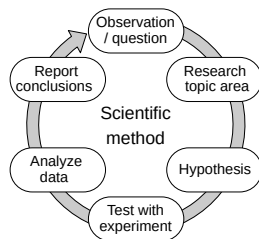
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- Mores in the field: End-to-end learning; 'bold' numbers on common datasets; trial and error; openly sharing code/weights/data; all papers open on ArXiv.

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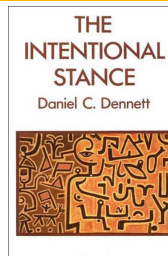
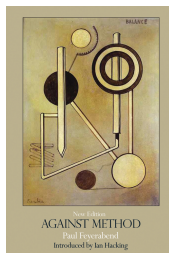
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# Against method: “*The Way*” vs “*A Way*”



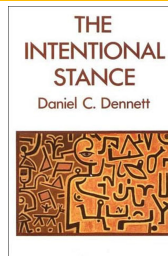
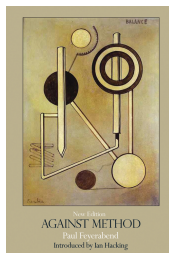
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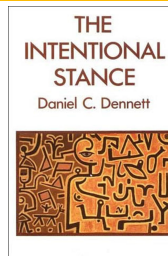
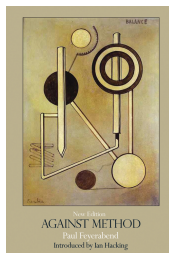
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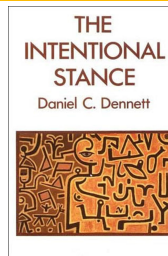
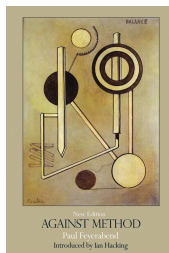
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Let people do research however they want (including yourself).

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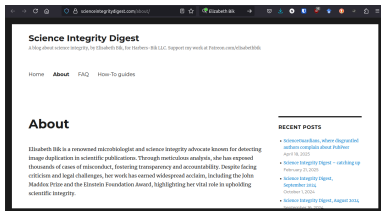
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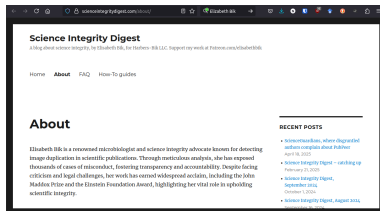
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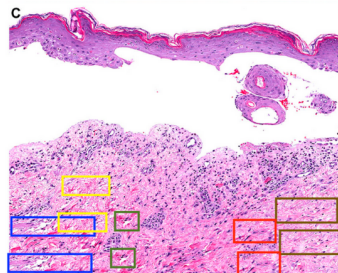
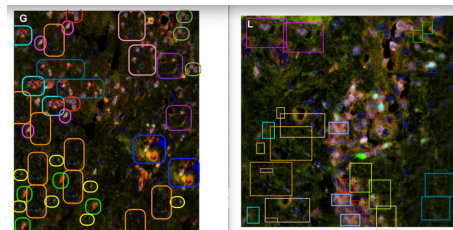
scienceintegritydigest.com

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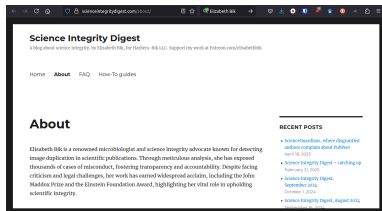


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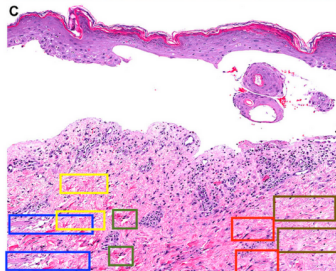
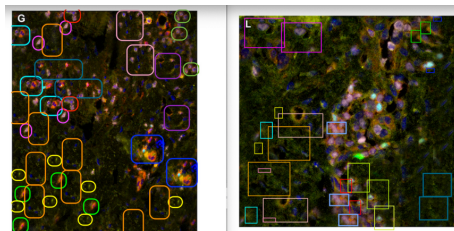
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Doesn't (only) preach "Don't do fraud; it's bad"<sup>1</sup>; she does the work.

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# My work for fundamental empirical research in ML/DL



## Reproduced Papers

Hub for reproduced deep learning papers and their reproductions

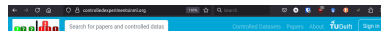
### Statistics

# Papers  
180

# Reproductions  
436

# Reproductions /  
Paper  
2.4

reproducedpapers.org



## Controlled Datasets

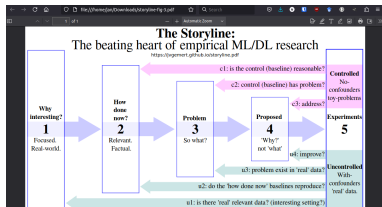
Hub for papers and associated controlled datasets

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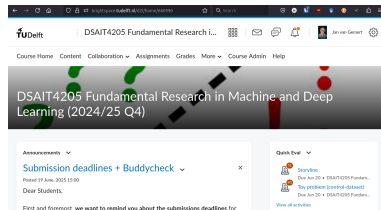
# Papers  
6

# Controlled Datasets  
4

controlledexperimentsinml.org



Online research guidelines



MSc course

# The last slide: end on a high note.

I don't believe:

- No single way to do science;
- No “*definition squabbling*” (we can't even define a chair).
- No preaching; let system builders build systems.

# The last slide: end on a high note.

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- No single way to do science;
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- No preaching; let system builders build systems.

I believe:

- ML/DL work is open as a field, openly sharing code, weights, papers.
- ML/DL misconduct (tune on the testset; cherry picking; plagiarism, overclaiming) is not as bad as elsewhere; limited direct fraud
- that the scientific method will correct things eventually.
- in “Be and let Be”. Let others do research their own way.
- in *doing*: help the ones that want to be helped.
- in moving constructively forward: Methodological development: reproducedpapers.org; controlledexperimentsinml.org; research guidelines; MSc course, this workshop, etc... (?)