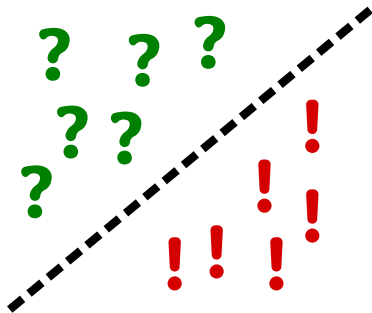


Metascience for ML

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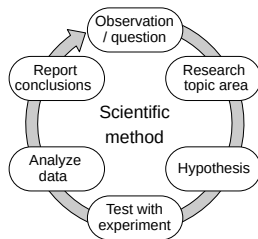
I would like to contribute to metascience for ML by...

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

The scientific method^[1] in times of deep learning

Deep learning powers AI; yet as a scientific field has growing pains^[2,3,4]



- 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.

[1]: https://en.wikipedia.org/wiki/Scientific_method

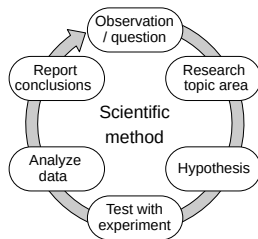
[2]: Lipton et al. "Troubling Trends in Machine Learning Scholarship", 2018.

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- ML/DL does not have many empirical theories.

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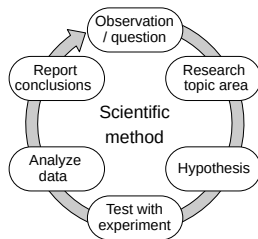
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 - Neural Scaling Laws;
 - Bias/variance
 - ML is like physics/neuroscience;
 - Simple axioms explaining intelligence
 - ...

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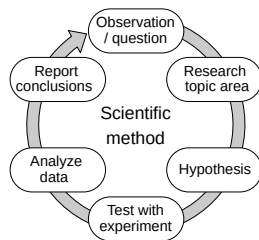
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- Mores in the field: End-to-end learning; 'bold' numbers on common datasets; trial and error; openly sharing code/weights/data; all papers open on ArXiv.

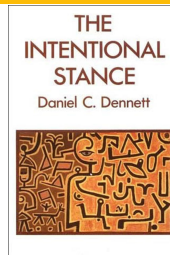
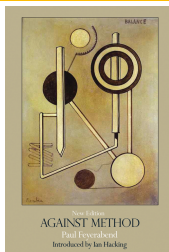
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Against method: “The Way” vs “A Way”

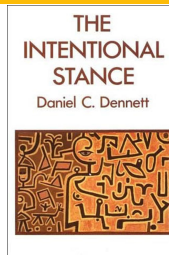
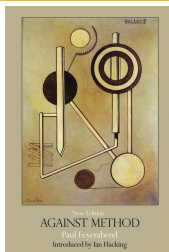


- There is not "one way" to do science. Science moves on, *despite* the methodology used^[5].

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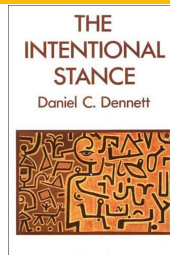
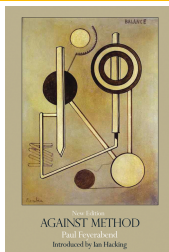


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- Squabbling over too crisp definitions gets us nowhere (we can't even define a 'chair'). If an LLM has 'intent', if it 'understands', if it is 'intelligent'. What is intended with these words is clear in context; using such words can even be useful for AI systems^[6].

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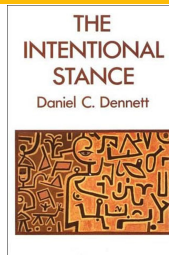
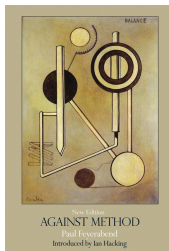


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Let people do research however they want (including yourself).

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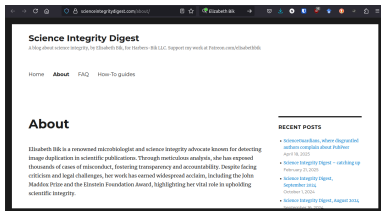
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My hero: Dr. Elizabeth Bik, science sleuth



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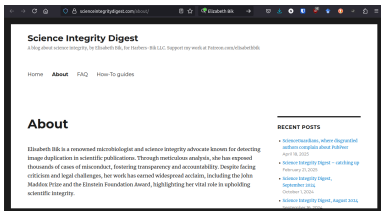
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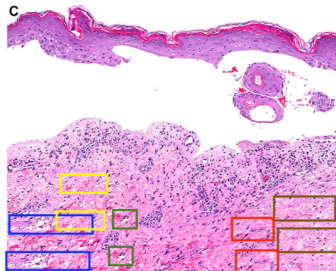
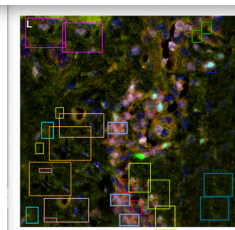
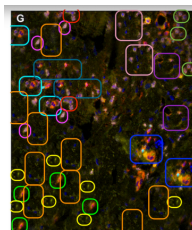
scienceintegritydigest.com

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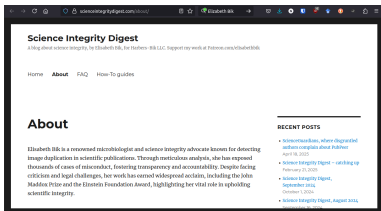


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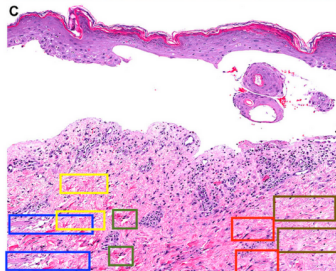
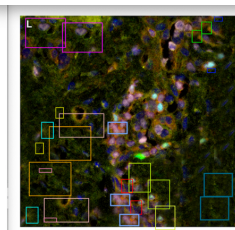
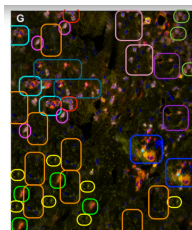
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Doesn't (only) preach "Don't do fraud; it's bad"¹; she does the work.

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My work for fundamental empirical research in ML/DL



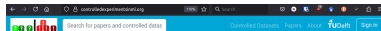
Reproduced Papers

Hub for reproduced deep learning papers and their reproductions

Statistics

# Papers	# Reproductions	# Reproductions / Paper
180	436	2.4

reproducedpapers.org



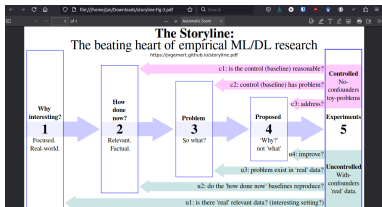
Controlled Datasets

Hub for papers and associated controlled datasets

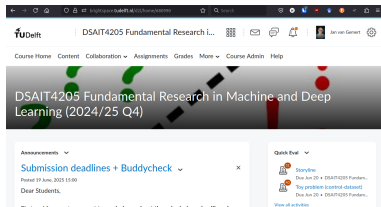
Statistics

# Papers	# Controlled Datasets
6	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 “*too crisp definition squabbling*” (we can't even define a chair).
- No preaching; let system builders build systems.

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- No single way to do science;
- No “*too crisp definition squabbling*” (we can't even define a chair).
- 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, ie: Do Something: my methodological development: reproducedpapers.org; controlledexperimentinml.org; research guidelines; MSc course, this workshop, etc... (?)