

A tale of two crises: COVID-19 and ML reproducibility

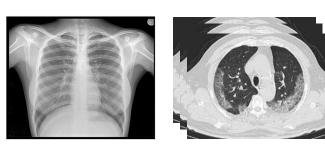
Trustworthy AI for Medical and Health Research Workshop

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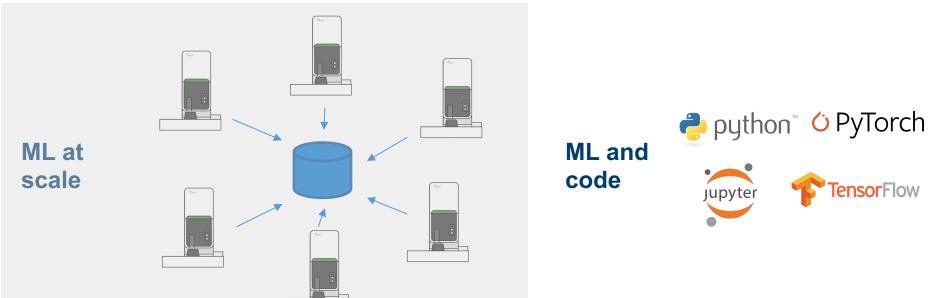
A pandemic of reproducibility issues

ML for COVID-19



ML for Incomplete Data



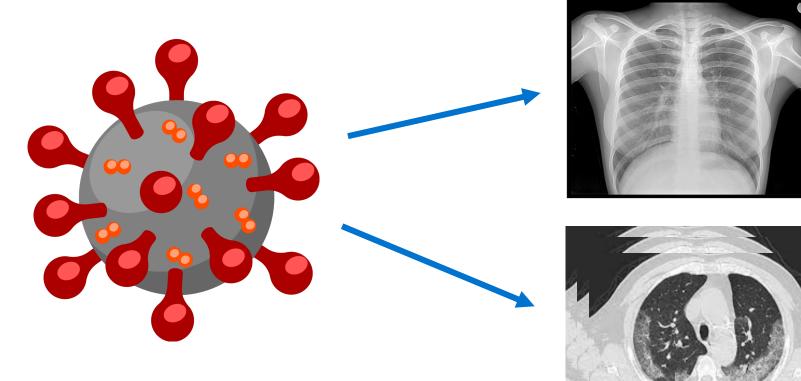




Issues with ...

Joint with Derek Driggs, Matthew Thorpe, Julian Gilbey, Angelica I. Aviles-Rivero, Cathal McCague, James Rudd, Evis Sala, Carola-Bibiane Schönlieb and many AIX-COVNET members

ML for COVID-19 imaging



Roberts, M., Driggs, D., Thorpe, M. et al. Common pitfalls and recommendations for using machine learning to detect and prognosticate for COVID-19 using chest radiographs and CT scans. Nature Machine Intelligence 3, 199–217 (2021). https://doi.org/10.1038/s42256-021-00307-0

nature machine intelligence

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COVID-19: A perfect test case for image based ML

- Never before have we had access to data:
 - at such scale for a single disease
 - all collected around the same time period
 - collected on the same machines
 - for a disease with a short infection time

So why did image based ML fail to contribute significantly to the COVID-19 pandemic?

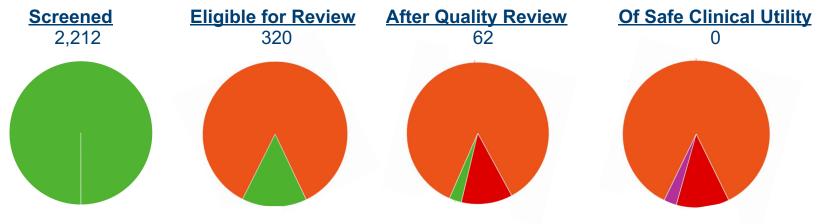


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Systematic Review

• Eligibility: Any papers using ML and CXR/CT imaging for COVID-19 diagnosis or prognosis.







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Basic pitfalls: Frankenstein datasets

• Know where your data comes from!

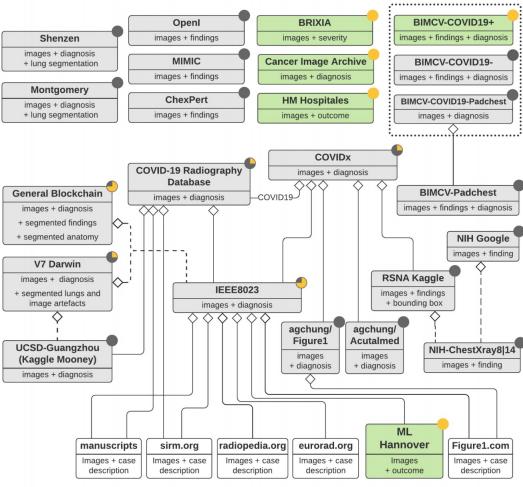




Figure from Cruz et al. (2021)



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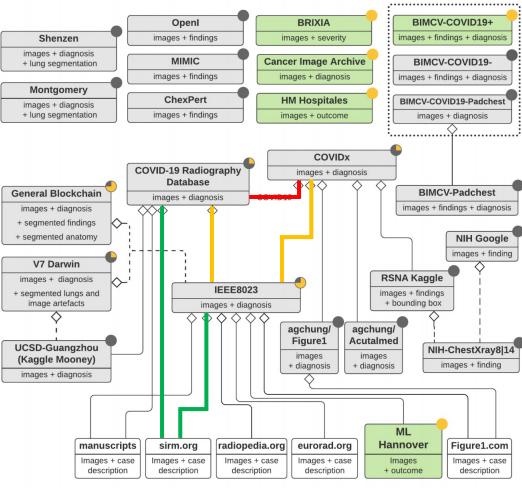




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Basic pitfalls: biases in images

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- Appreciate the biases in your data.



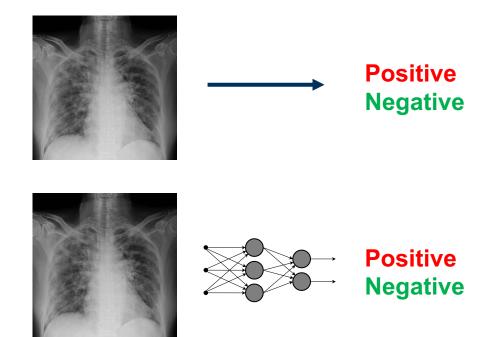




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Basic pitfalls: biases in labels

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- Appreciate the biases in your data.
- Ground truth assigned based on images.



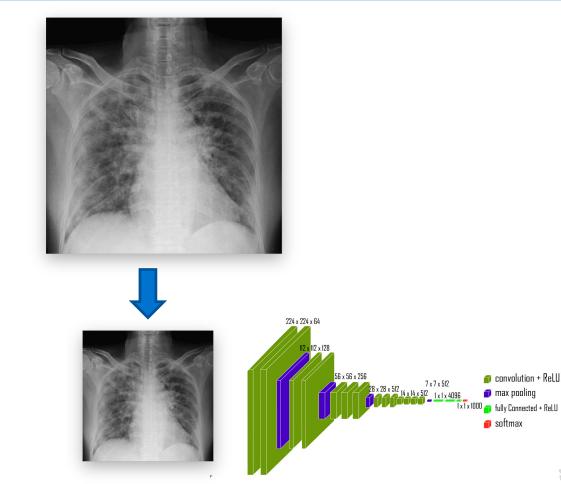


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Basic pitfalls: biases in models

- Know where your data comes from!
- Appreciate the biases in your data.
- Ground truth assigned based on images.
- Resolution driven by pretrained networks





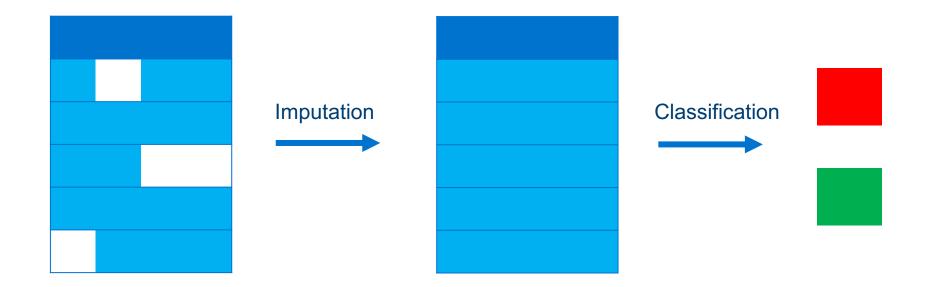
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Joint with Tolou Shadbahr, Julian Gilbey, Jan Stanczuk, Philip Teare, Sören Dittmer, John Aston, Carola-Bibiane Schönlieb and many AIX-COVNET members

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• QRISK is a model for predicting your risk of a cardiovascular disease.

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- After improving the imputation method, the link to cholesterol was recovered.
- An improved algorithm is now a standard used in the UK NHS.

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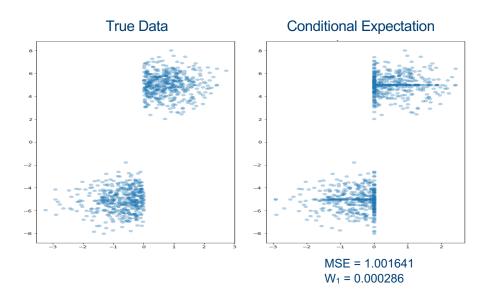
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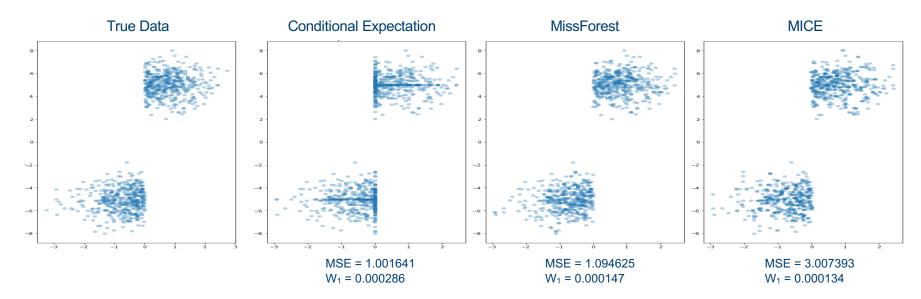


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What are the issues?

- We find that many new methods fail both to:
 - recreate data distributions
 - give stable imputations
- This compromises model interpretability
- Missingness may be informative for the models



Issues with ...

Joint with Sören Dittmer, James Rudd, John Aston, Carola-Bibiane Schönlieb

ML and code





O PyTorch



Dittmer, S.*, **Roberts, M.***,., ... & Schönlieb, C.-B. Navigating the challenges in creating complex data systems: a development philosophy (2022). Under Review. *arXiv:2210.13191*.

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Marauding as software engineers



10 years ago, this was a software engineer....



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Marauding as software engineers



10 years ago, this was a software engineer....

Now it is also a:

- Data scientist
- Mathematician
- Statistician
- Machine learning engineer



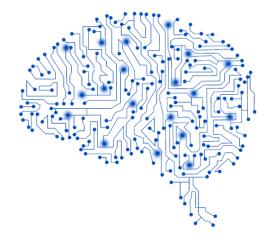
An explosion of data and sources

We must often structure and preprocess this data ourselves

Without deep domain knowledge, we have lost control of the biases in the data



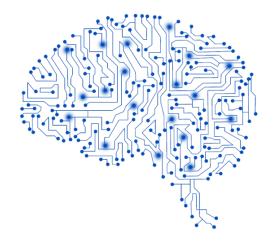


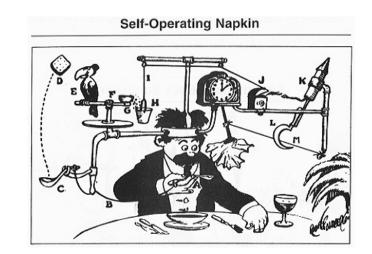


Idealistic illustration of machine learning



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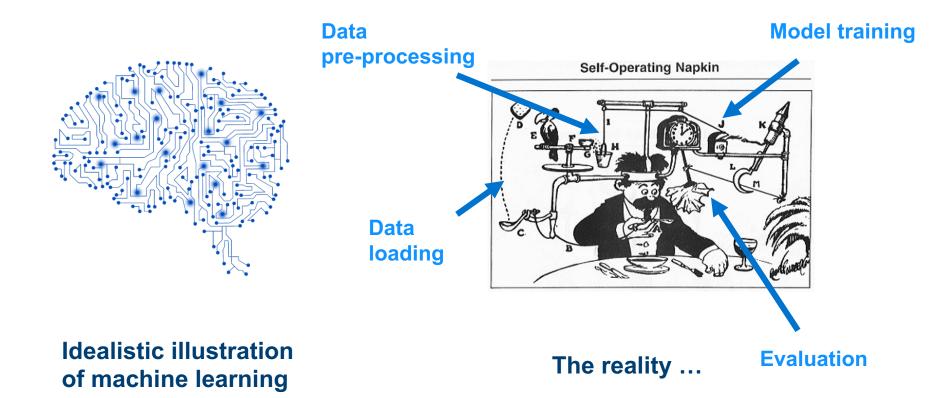


Idealistic illustration of machine learning

The reality ...



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Typical workflow for an ML project

- Code is built as a monolith
- It is tinkered with until it stops giving errors
- Train using all the data and then analyse the results

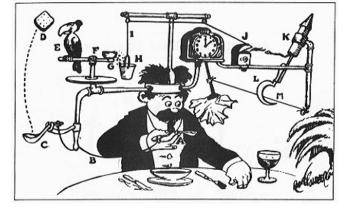




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- If you don't enforce your assumptions in the code, someone will break it



Thank you