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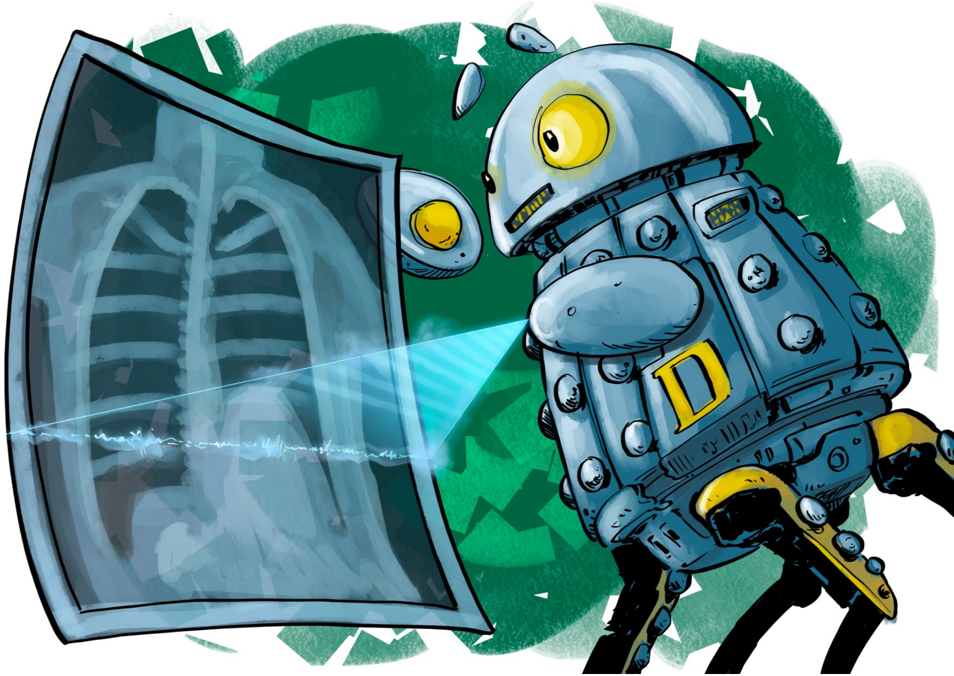
Jak budować skuteczne i bezpieczne modele uczenia maszynowego dla zastosowań medycznych

How to build trustworthy machine learning models for medical applications



Przemysław Biecek

Projekt: Godna zaufania sztuczna inteligencja wspierająca identyfikację zmian chorobowych w płucach na bazie danych obrazowych
INFOSTRATEG-I/0022/2021

22.06.2022

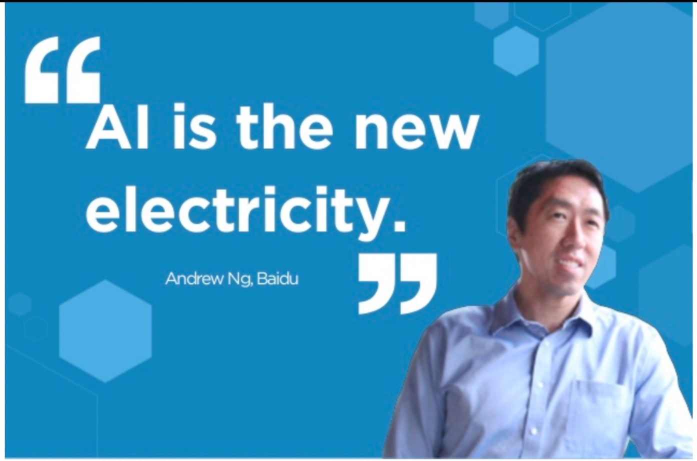
About me and MI^2.ai

Associate professor at University of Warsaw and Warsaw University of Technology
Past: Samsung, Netezza, IBM, Disney, iQor

Research area: **Human Oriented AI**

Research projects:
MLGenSig (NCN), DALEX (NCN), HOMER (NCN), DeCovid (IDUB)
X-LUNGS (NCBiR): Responsible Artificial Intelligence for Lung Diseases

Where we are with AI?



https://www.slideshare.net/jaypod/digitaltransformation50soundbites/19-Data_is_the_new_oilClive
https://www.newworldai.com/forget-the-hype-what-every-business-leader-needs-to-know-about-artificial-intelligence-now/

Where we are with AI?

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List of failures in AI applications

Read more at: https://romanlutz.github.io/ResponsibleAI/

Speech Detection

- Oh dear... AI models used to flag hate speech online are, er, racist against black people
- The Risk of Racial Bias in Hate Speech Detection
- Toxicity and Tone Are Not The Same Thing: analyzing the new Google API on toxicity, PerspectiveAPI.
- Voice Is the Next Big Platform, Unless You Have an Accent
- Google's speech recognition has a gender bias
- Fair Speech report by Stanford Computational Policy Lab, also covered in Speech recognition algorithms may also have racial bias
- Automated moderation tool from Google rates People of Color and gays as "toxic"
- Someone made an AI that predicted gender from email addresses, usernames. It went about as well as expected

Image Labelling & Face Recognition

- Google Photos identified two black people as 'gorillas'
- When It Comes to Gorillas, Google Photos Remains Blind
- The viral selfie app ImageNet Roulette seemed fun – until it called me a racist slur
- Google Is Investigating Why it Trained Facial Recognition on 'Dark Skinned' Homeless People
- Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification
- Machines Taught by Photos Learn a Sexist View of Women
- Tenants sounded the alarm on facial recognition in their buildings. Lawmakers are listening.
- Google apologizes after its Vision AI produced racist results

Public Benefits & Health

governmentCIO MEDIA & RESEARCH

Topics Video Events Podcasts

Machine Learning is Creating a Crisis in Science

The adoption of machine-learning techniques is contributing to a worrying number of research findings that cannot be repeated by other researchers.

Kevin McCaney
Wed, 02/27/2019 - 11:28

Photo credit: metamorworks/iStock

Do we have a problem?

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Results: We identified 27 697 patients who had 38 455 hospitalizations (21 904 women [57%]; median age, 56 years [interquartile range, 35-69 years]) meeting inclusion criteria, of whom sepsis occurred in 2552 (7%). The ESM had a hospitalization-level area under the receiver operating characteristic curve of 0.63 (95% CI, 0.62-0.64). The ESM identified 183 of 2552 patients with sepsis (7%) who did not receive timely administration of antibiotics, highlighting the low sensitivity of the ESM in comparison with contemporary clinical practice. The ESM also did not identify 1709 patients with sepsis (67%) despite generating alerts for an ESM score of 6 or higher for 6971 of all 38 455 hospitalized patients (18%), thus creating a large burden of alert fatigue.

Conclusions and relevance: This external validation cohort study suggests that the ESM has poor discrimination and calibration in predicting the onset of sepsis. The widespread adoption of the ESM despite its poor performance raises fundamental concerns about sepsis management on a national level.

https://pubmed.ncbi.nlm.nih.gov/34152373/

	Epic +	Epic –	Total
Sepsis	843	1,709	2,552
No Sepsis	6,128	29,775	35,903
Total	6,971	31,484	38,455

a. Of the 2,552 patients with sepsis, ESM only generated sepsis alerts for 843 (33 percent). They missed 67 percent of the people with sepsis.

b. Of the 6,971 ESM sepsis alerts, only 843 (12 percent) were correct; 88 percent of the ESM sepsis alerts were false alarms, creating what the authors called “a large burden of alert fatigue.”

https://mindmatters.ai/2021/08/an-epic-failure-overstated-ai-claims-in-medicine/

Do we have a problem?

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IBM spent more than $15 billion on Dr. Watson with no peer-reviewed evidence that it improved patient health outcomes. Watson Health has disappointed so soundly that IBM is now looking for someone to take it off their hands.

> Five years and $60 million later, MD Anderson fired Watson after "multiple examples of unsafe and incorrect treatment recommendations."

Dr. Watson was the most hyped computerized health care system, but it is hardly the only disappointing one. Most recently, a 2021 study looked at 2,212 research papers published during the period from January 1, 2020, to October 3, 2020, that described new machine learning models for diagnosing or prognosing COVID-19 from chest radiographs and chest computed tomography images. Their conclusion: "None of the models identified are of potential clinical use."

https://mindmatters.ai/2021/03/doctors-wont-be-obsolete-anytime-soon/

AI act to the rescue!

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EUROPEAN COMMISSION

Brussels, 21.4.2021

COM(2021) 206 final

2021/0106(COD)

Proposal for a

REGULATION OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL

LAYING DOWN HARMONISED RULES ON ARTIFICIAL INTELLIGENCE (ARTIFICIAL INTELLIGENCE ACT) AND AMENDING CERTAIN UNION LEGISLATIVE ACTS

{SEC(2021) 167 final} - {SWD(2021) 84 final} - {SWD(2021) 85 final}

EXPLANATORY MEMORANDUM

1. CONTEXT OF THE PROPOSAL

1.1. Reasons for and objectives of the proposal

This explanatory memorandum accompanies the proposal for a Regulation laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). Artificial Intelligence (AI) is a fast evolving family of technologies that can bring a wide array of economic and societal benefits across the entire spectrum of industries and social activities. By improving prediction, optimising operations and resource allocation, and personalising service delivery, the use of artificial intelligence can support socially and environmentally beneficial outcomes and provide key competitive

The Regulatory Framework
4 levels of risk in AI:

Unacceptable risk
High risk
Limited risk
Minimal or no risk

Important but overlooked aspects

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To build a good AI system it is needed to take care of:

- high quality **data**
- methods of reducing undesired **bias**
- methods of exploring and **explaining** models
- many other topics that I will not talk about today

Data is King

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Analysis | Open Access | Published: 15 March 2021

Common pitfalls and recommendations for using machine learning to detect and prognosticate for COVID-19 using chest radiographs and CT scans

Michael Roberts, Derek Driggs, Matthew Thorpe, Julian Gilbey, Michael Yeung, Stephan Ursprung, Angelica I. Aviles-Rivero, Christian Etmann, Cathal McCague, Lucian Beer, Jonathan R. Weir-McCall, Zhongzhao Teng, Effrossyni Gkrania-Klotsas, AIX-COVNET, Jame

Bibiane Schönlieb

Nature Machine Intelligence **3**, 199–217 (2021) | Cite this article

Recommendations for data

First, we advise caution over the use of public repositories, which can lead to high risks of bias due to source issues and Frankenstein datasets as discussed above. Furthermore, authors should aim to match demographics across cohorts, an often neglected but important potential source of bias; this can be impossible with public datasets that do not include demographic information, and including paediatric images[86] in the COVID-19 context introduces a strong bias.

Using a public dataset alone without additional new data can lead to community-wide overfitting on this dataset. Even if each individual study observes sufficient precautions to avoid overfitting, the fact that the community is focused on outperforming benchmarks on a single public dataset encourages overfitting. Many public datasets containing images taken from preprints receive these images in low-resolution or compressed formats (for example

Data is King

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Prediction models for diagnosis and prognosis of covid-19: systematic review and critical appraisal

Laure Wynants,[1,2] Ben Van Calster,[2,3] Gary S Collins,[4,5] Richard D Riley,[6] Georg Heinze,[7] Ewoud Schuit,[8,9] Marc M J Bonten,[8,10] Darren L Dahly,[11,12] Johanna A Damen,[8,9] Thomas P A Debray,[8,9] Valentijn M T de Jong,[8,9] Maarten De Vos,[2,13] Paula Dhiman,[4,5] Maria C Haller,[7,14] Michael O Harhay,[15,16] Liesbet Henckaerts,[17,18] Pauline Heus,[8,9] Michael Kammer,[7,19] Nina Kreuzberger,[20] Anna Lohmann,[21] Kim Luijken,[21] Jie Ma Glen P Martin,[22] David J McLernon,[23] Constanza L Andaur Navarro,[8,9] Johannes E Jamie C Sergeant,[24,25] Chunhu Shi,[26] Nicole Skoetz,[19] Luc J M Smits,[1] Kym I E Sne Matthew Sperrin,[27] René Spijker,[8,9,28] Ewout W Steyerberg,[3] Toshihiko Takada,[8] Ioanna Tzoulaki,[29,30] Sander M J van Kuijk,[31] Bas C T van Bussel,[1,32] Iwan C C var Florien S van Royen,[8] Jan Y Verbakel,[33,34] Christine Wallisch,[7,35,36] Jack Wilkinson Robert Wolff,[37] Lotty Hooft,[8,9] Karel G M Moons,[8,9] Maarten van Smeden[8]

https://www.bmj.com/content/bmj/369/bmj.m1328.full.pdf

Cite this as: *BMJ* 2020;369:m1328
http://dx.doi.org/10.1136/bmj.m1328

Originally accepted:
31 March 2020

Final version accepted:
12 January 2021

Conclusion

Several diagnostic and prognostic models for covid-19 are currently available and they all report moderate to excellent discrimination. However, these models are all at high or unclear risk of bias, mainly because of model overfitting, inappropriate model evaluation (eg, calibration ignored), use of inappropriate data sources and unclear reporting. Therefore, their performance estimates are probably optimistic and not representative for the target population. The COVID-PRECISE group does not recommend any of the current prediction models to be used in practice, but one

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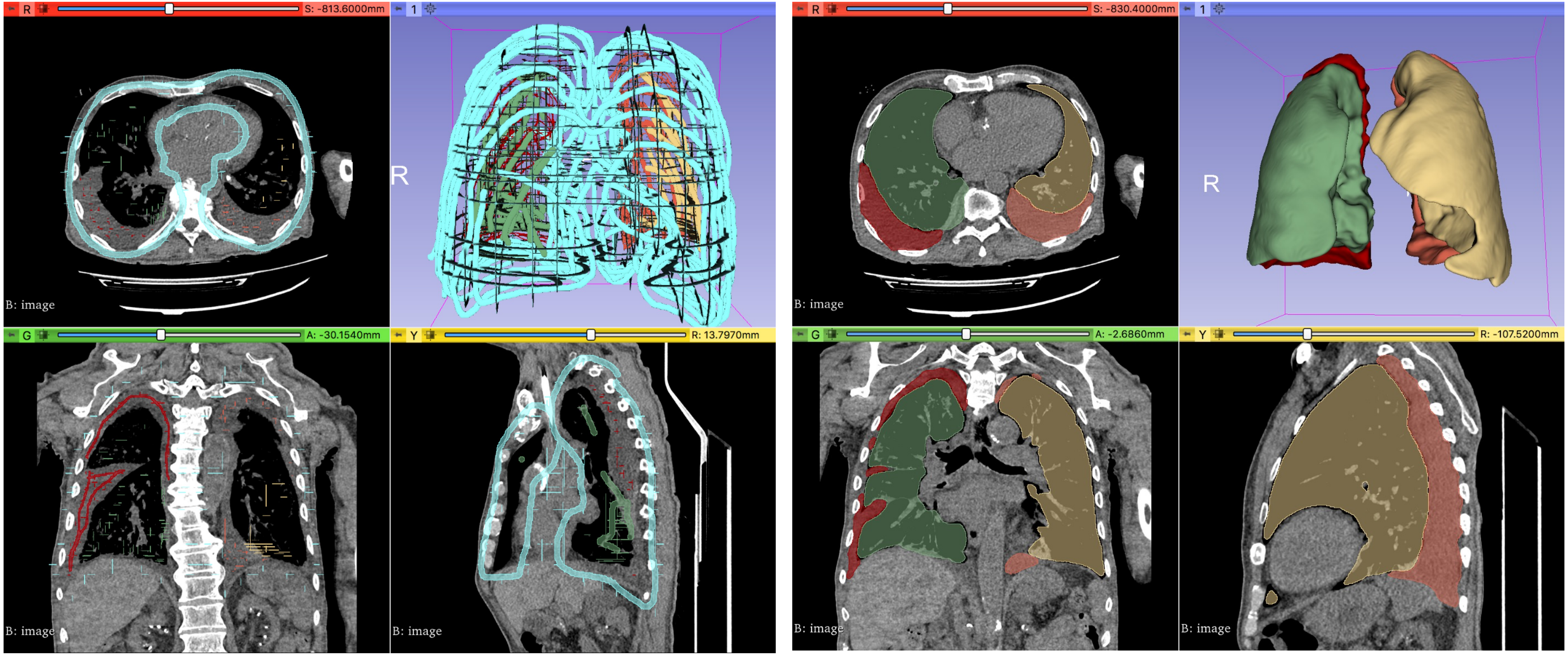
- We prepared a dataset with more than 40,000 CT scans (plus xrays).
- The data is representative of the Polish population.
- **Data will be made public** for other teams soon.
- We will also prepare a special benchmark allowing for proper validation of the developed solutions.

https://medium.com/responsibleml/towards-the-largest-database-of-polish-lung-medical-images-13df8c2b1695

Data is King



- The data have different modalities (series of images + text medical records + tabular data).
- And we have identified over 30 different tasks for them.
- The tasks vary from binary classification to regression to segmentation.

https://medium.com/responsibleml/radiologists-nightmare-segmentation-masks-10581ae9310

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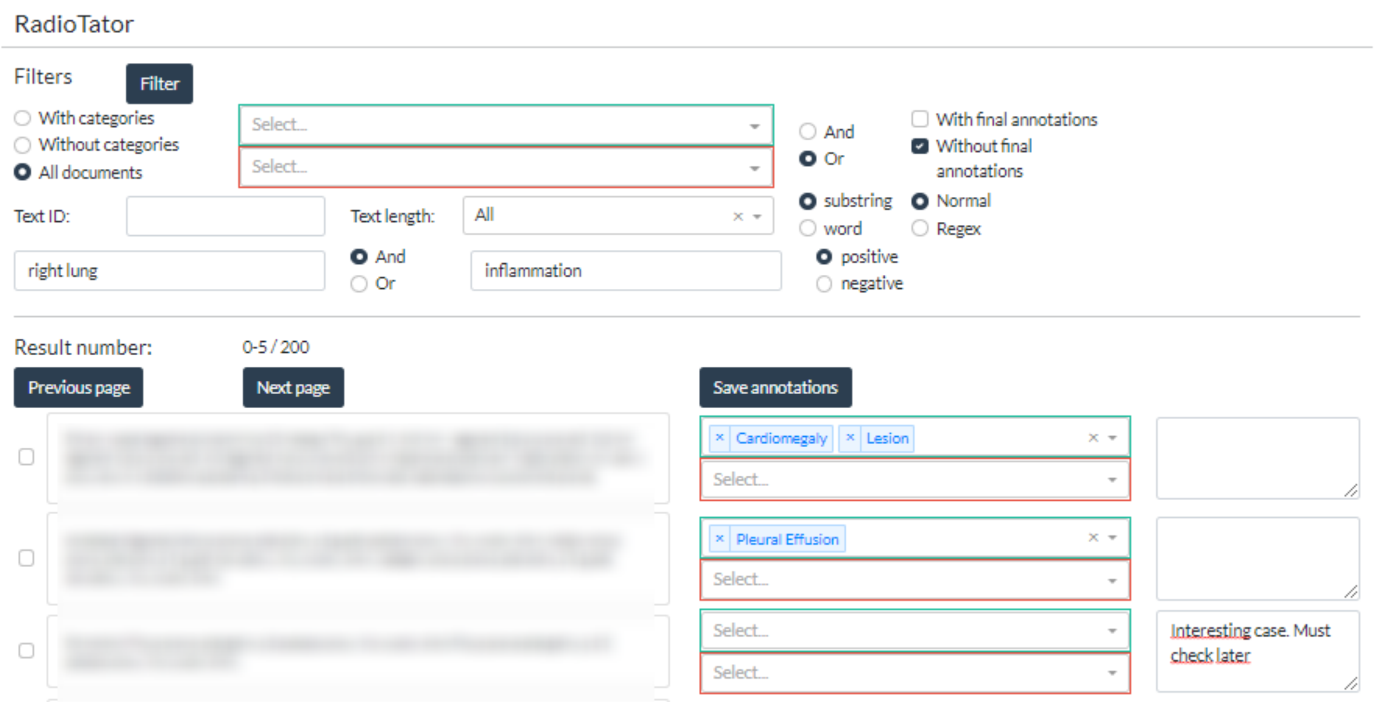

- Very often, relevant information is stored in plain text descriptions.
- And these descriptions may be very diverse.
- Extracting structures data can be aided by applying advanced NLP techniques
- In the picture you can see the RadioTator that we developed for more efficient extraction of data from text

https://medium.com/responsibleml/a-tailored-tool-for-rapid-medical-text-annotation-f756c1e06d64

Important but overlooked aspects

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To build a good AI system it is needed to take care of:

- high quality **data**
- methods of reducing undesired **bias**
- methods of exploring and **explaining** models
- many other topics that I will not talk about today

Recurring Nightmares: Bias

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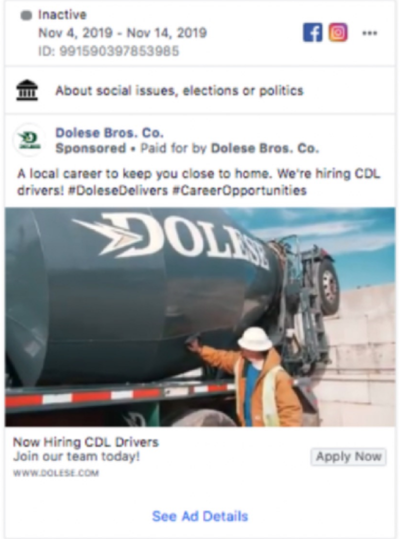
MACHINE BIAS

Facebook Ads Can Still Discriminate Against Women and Older Workers, Despite a Civil Rights Settlement

New research and Facebook's own ad archive show that the company's new system to ensure diverse audiences for housing and employment ads has many of the same problems as its predecessor.

by Ava Kofman and Ariana Tobin, Dec. 13, 2019, 5 a.m. EST



Left: A Facebook ad for Dolese Bros. Co. Right: Facebook's chart shows that 87 percent of the people who saw the ad were men.

https://www.propublica.org/article/facebook-ads-can-still-discriminate-against-women-and-older-workers-despite-a-civil-rights-settlement

Recurring Nightmares: Bias

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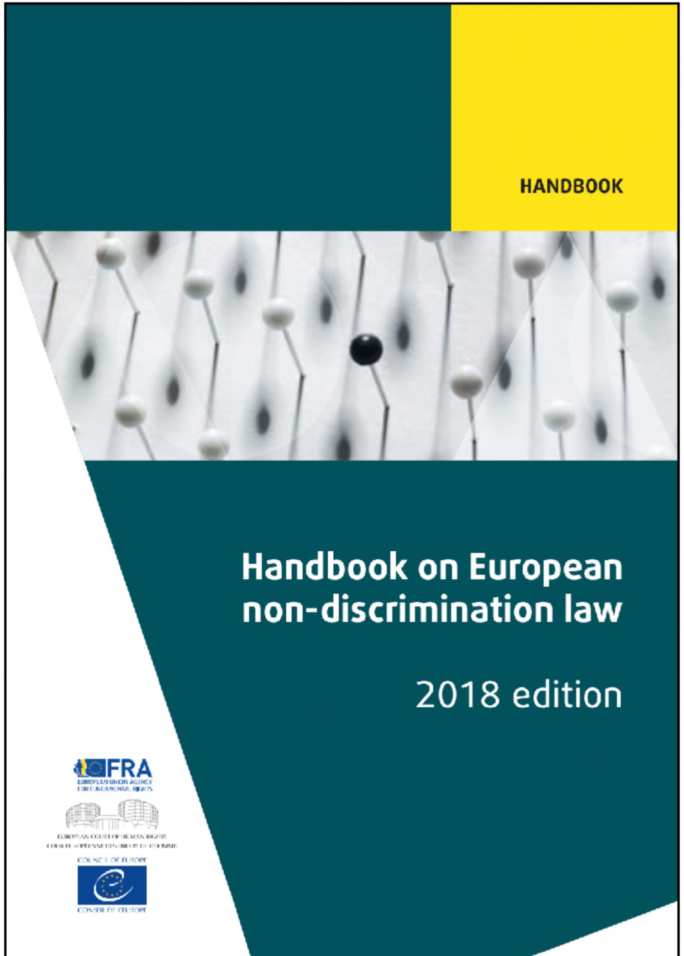
Key point

- Discrimination defines a situation where an individual is disadvantaged in some way on the basis of 'one or multiple protected grounds'.

PROTECTED GROUNDS
- Sex
- Gender identity
- Sexual orientation
- Disability
- Age
- Race, ethnicity, colour and membership of a national minority
- Nationality or national origin
- Religion or belief
- Social origin, birth and property
- Language
- Political or other opinion

https://fra.europa.eu/sites/default/files/fra_uploads/fra-2018-handbook-non-discrimination-law-2018_en.pdf

https://fra.europa.eu/en/publication/2018/handbook-european-non-discrimination-law-2018-edition



Recurring Nightmares: Bias

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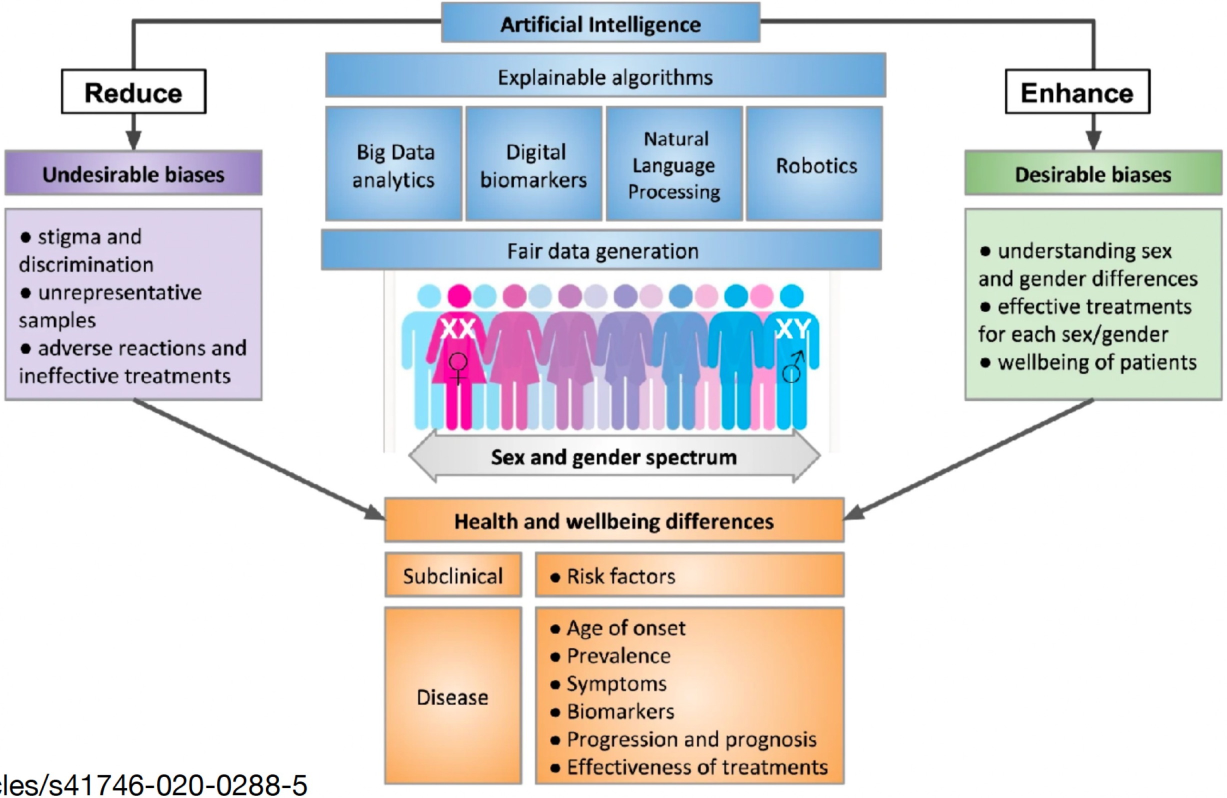
Sex and gender differences and biases in artificial intelligence for biomedicine and healthcare

Cirillo et al 2020



https://www.nature.com/articles/s41746-020-0288-5

Recurring Nightmares: Bias

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Sex and gender differences and biases in artificial intelligence for biomedicine and healthcare

Cirillo et al 2020

Clinical conditions and studies	Current status without the desirable bias	Utility of the desirable bias
Autistic spectrum disorder	There is a current lack of consideration of the demonstrated age-dependent sex differences in the symptomatology related with impairments in social communication and interaction, expressive behaviour, reciprocal conversation, non-verbal gestures for diagnostic purposes[123].	Differential diagnostic criteria for males and females could facilitate the identification of the clinical diagnosis leading to appropriate treatment.
Cardiovascular disorders	Although it has been documented that men and women respond differently to many cardiovascular medications such as statins, angiotensin-converting enzyme inhibitors and β-Blockers among others, adopted treatments do not consider sex differences[124].	Making prescriptions according to the sex of the patient could lead to improved health benefits.
	Despite the fact that Coronary heart disease (CHD) is the leading cause of death among women[125], the majority (67%) of patients enroled in clinical trials for cardiovascular devices are male[126].	The application of a desirable bias towards women would lead to a more accurate representation of sex differences in clinical research.
Genome-wide association studies (GWAS)	Most of genome-wide association studies (GWAS) focus on white male subjects[127] and those that explore sex differences in complex traits are scarce[128].	The introduction of desirable biases to deliberately include female subjects and other ethnicities in GWAS could lead to better account for potential sex differences in disease that are currently unknown because of being overlooked.
Human immunodeficiency virus (HIV)	The observed lower female representation in HIV clinical trials depends, among other factors, from the disadvantaged awareness about treatment and enrolment options compared with men[129–131].	Promoting empowerment initiatives in those patients with disadvantages will increase their exposure to treatment options and clinical trial enrolment.

https://www.nature.com/articles/s41746-020-0288-5

Recurring Nightmares: Bias

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- **Historical bias.** The data are correctly sampled and correspond well to the observed relationships, but due to different treatment in the past some prejudices are encoded in the data. Think about gender and occupation stereotypes.
- **Representation bias.** The available data is not a representative sample of the population of interest. Think about the available facial images of actors, often white men. Or genetic sequences of covid variants, mostly collected in developed European countries. Or crime statistics in the regions to which the police are directed.
- **Measurement bias.** The variable of interest is not directly observable or is difficult to measure and the way it is measured may be distorted by other factors. Think of the results of the mathematics skills assessment (e.g. PISA) measured by tasks on computers not that widely available in some countries.
- **Evaluation bias.** The evaluation of the algorithm is performed on a population that does not represent all groups. Think of a lung screening algorithm tested primarily on a population of smokers (older men).
- **Proxy bias.** The algorithm uses variables that are proxies for protected attributes. Think of male/female only schools where the gender effect can be hidden under the school effect.

partially based on Cirillo et al, 2020. https://www.nature.com/articles/s41746-020-0288-5

Recurring Nightmares: Bias

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Group fairness / statistical parity / independence / demographic parity

$$P(\widehat{Y} = 1 | A = a) = P(\widehat{Y} = 1 | A = b) \qquad \widehat{Y} \perp A$$

Predicted class is independent from protected attribute

	$Y = 1$	$Y = 0$	
$\widehat{Y} = 1$	TP	FP	P
$\widehat{Y} = 0$	FN	TN	N
	π_1	π_0	

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Equalized odds, Separation, Positive Rate Parity

$$P(\widehat{Y}=1|A=a,Y=1)=P(\widehat{Y}=1|A=b,Y=1)$$
$$P(\widehat{Y}=1|A=a,Y=0)=P(\widehat{Y}=1|A=b,Y=0)$$

$$\widehat{Y} \perp A \mid Y$$

Equal True Positive Rate TPR = TP/(TP+FN) for each subgroup and

equal False Positive Rate FPR = FP/(FP+TN) for each subgroup

Predicted class is independent from protected attribute given true class

	$Y=1$	$Y=0$	
$\widehat{Y}=1$	TP	FP	P
$\widehat{Y}=0$	FN	TN	N
	π_1	π_0	

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Predictive Rate Parity, Sufficiency

$$P(Y=1|A=a,\widehat{Y}=1)=P(Y=1|A=b,\widehat{Y}=1)$$
$$P(Y=1|A=a,\widehat{Y}=0)=P(Y=1|A=b,\widehat{Y}=0)$$

$$Y \perp A \mid \widehat{Y}$$

Equal Positive Predictive Value PPV = TP / (TP + FP) for each subgroup and

equal Negative Predictive Value NPV = NP / (NP + NP) for each subgroup

True class is independent from protected attribute given predicted class

	$Y=1$	$Y=0$	
$\widehat{Y}=1$	TP	FP	P
$\widehat{Y}=0$	FN	TN	N
	π_1	π_0	

Recurring Nightmares: Bias

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COMPAS case

Demographic parity:

frequency of convicted by the court equal for each subpopulation

fair from society's perspective

	$Y=1$	$Y=0$	
$\hat{Y}=1$	TP	FP	P
$\hat{Y}=0$	FN	TN	N
	π_1	π_0	

Equal opportunity:

frequency of convicted among innocents equal for all subpopulations

fair from the prisoner's perspective (ProPublica)

	$Y=1$	$Y=0$	
$\hat{Y}=1$	TP	FP	P
$\hat{Y}=0$	FN	TN	N
	π_1	π_0	

Predictive Rate Parity:

frequency of innocents among convicts is equal for subpopulations

fair from the judge's perspective (Northpointe)

	$Y=1$	$Y=0$	
$\hat{Y}=1$	TP	FP	P
$\hat{Y}=0$	FN	TN	N
	π_1	π_0	

Recurring Nightmares: Bias

COMPAS case

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$\hat{Y}=0$	FN	TN	N
		π_0	

Equal opportunity:

frequency of convicted an
for all subpopulations

fair from the prisoner's pers

		$=0$	
		FP	P
		TN	N
		π_0	

The fairness trade-off (fairml.org)

Except in trivial situations, you cannot control all three criteria.

In most cases, you can't even control two of them.

Predictive Rate Parity:

frequency of innocents among convicts is equal for subpopulations

fair from the judge's perspective (Northpointe)

	$Y=1$	$Y=0$	
$\hat{Y}=1$	TP	FP	P
$\hat{Y}=0$	FN	TN	N
	π_1	π_0	

Recurring Nightmares: Bias

MI × LUNGS

arXiv.org > stat > arXiv:2104.00507

Search...

Help | Advanc

Statistics > Machine Learning

[Submitted on 1 Apr 2021]

fairmodels: A Flexible Tool For Bias Detection, Visualization, And Mitigation

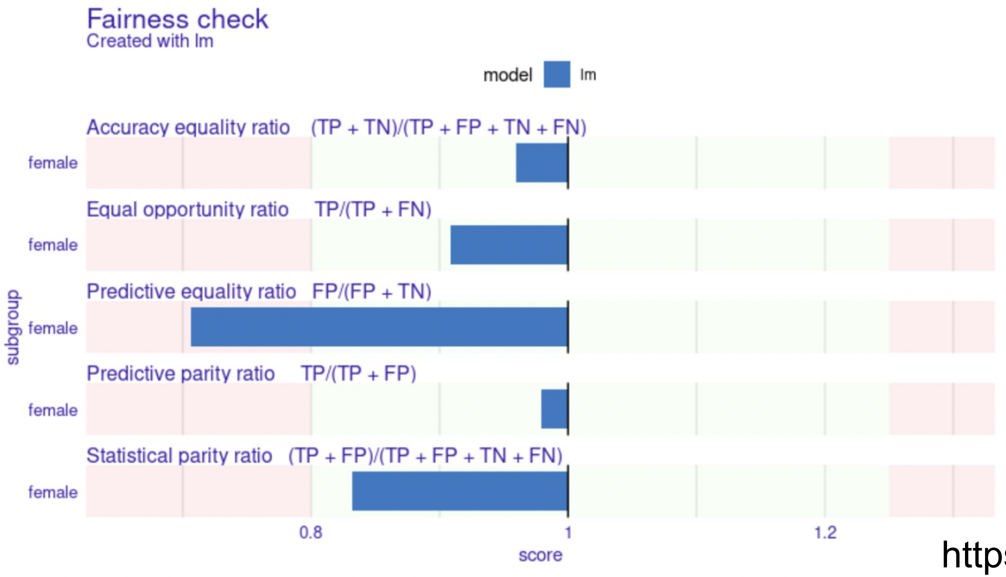
Jakub Wiśniewski, Przemysław Biecek

Machine learning decision systems are getting omnipresent in our lives. From dating apps to rating loan seekers, algorithms affect both our well-being and future. Typically, however, these systems are not infallible. Moreover, complex predictive models are really eager to learn social biases present in historical data that can lead to increasing discrimination. If we want to create models responsibly then we need tools for in-depth validation of models also from the perspective of potential discrimination. This article introduces an R package fairmodels that helps to validate fairness and eliminate bias in classification models in an easy and flexible fashion. The fairmodels package offers a model-agnostic approach to bias detection, visualization and mitigation. The implemented set of functions and fairness metrics enables model fairness validation from different perspectiv
The package is designed not only to examine a sin

Comments: 15 pages, 9 figures
Subjects: **Machine Learning (stat.ML)**; Machine Learning (
Cite as: arXiv:2104.00507 **[stat.ML]**
(or arXiv:2104.00507v1 **[stat.ML]** for this versior

Submission history

From: Przemyslaw Biecek [view email]
[v1] Thu, 1 Apr 2021 15:06:13 UTC (1,920 KB)



https://fairmodels.drwhy.ai/

Important but overlooked aspects

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To build a good AI system it is needed to take care of:

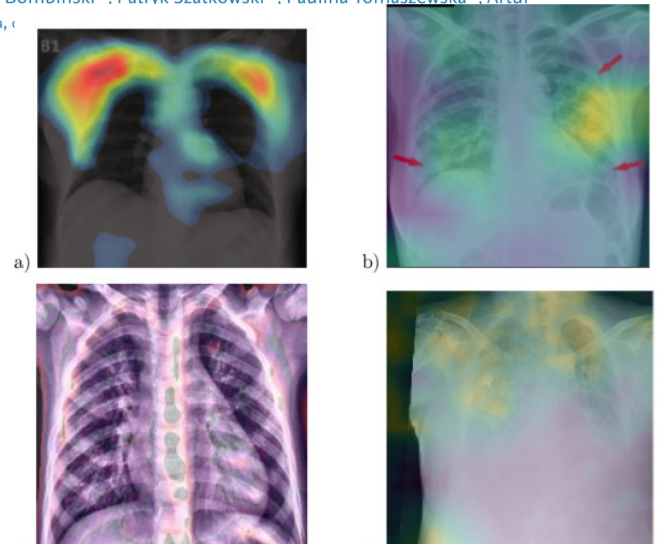
- high quality **data**
- methods of reducing undesired **bias**
- methods of exploring and **explaining** models
- many other topics that I will not talk about today

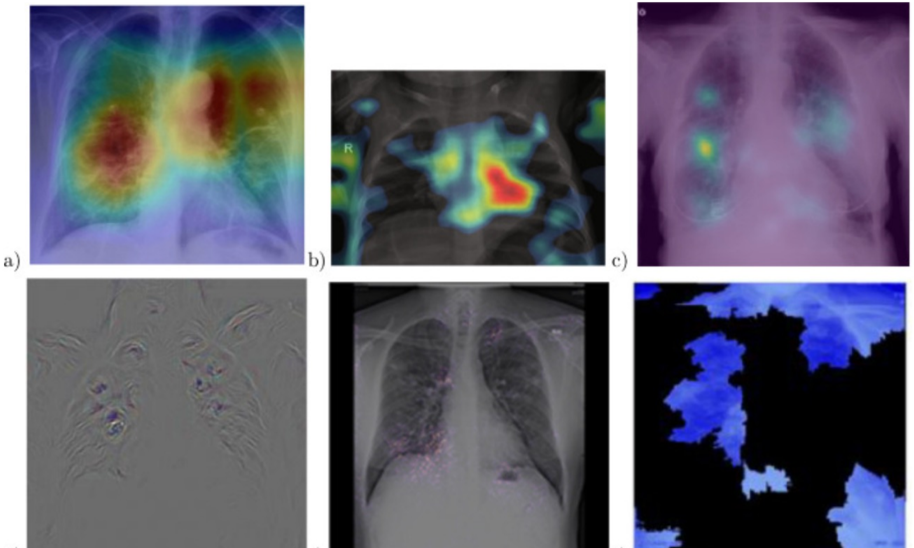
Explain!

Pattern Recognition
Volume 118, October 2021, 108035

Checklist for responsible deep learning modeling of medical images based on COVID-19 detection studies

Weronika Hryniewska [a], Przemysław Bombiński [b], Patryk Szatkowski [b], Paulina Tomaszewska [a], Artur Przelaskowski [a], Przemysław Biecek [a,





Explain!

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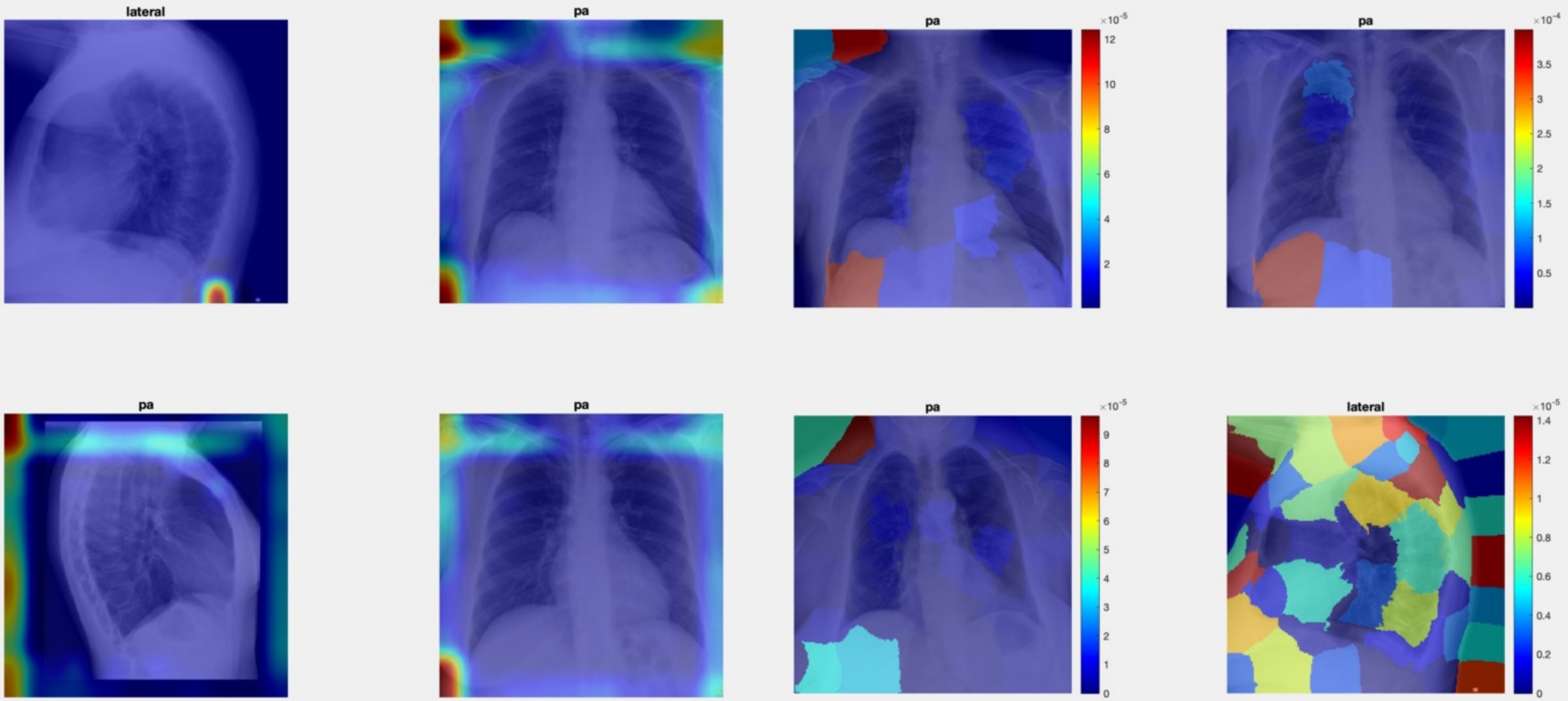

https://www.datasciencecentral.com/explainable-ai-for-medical-images/

Explain!

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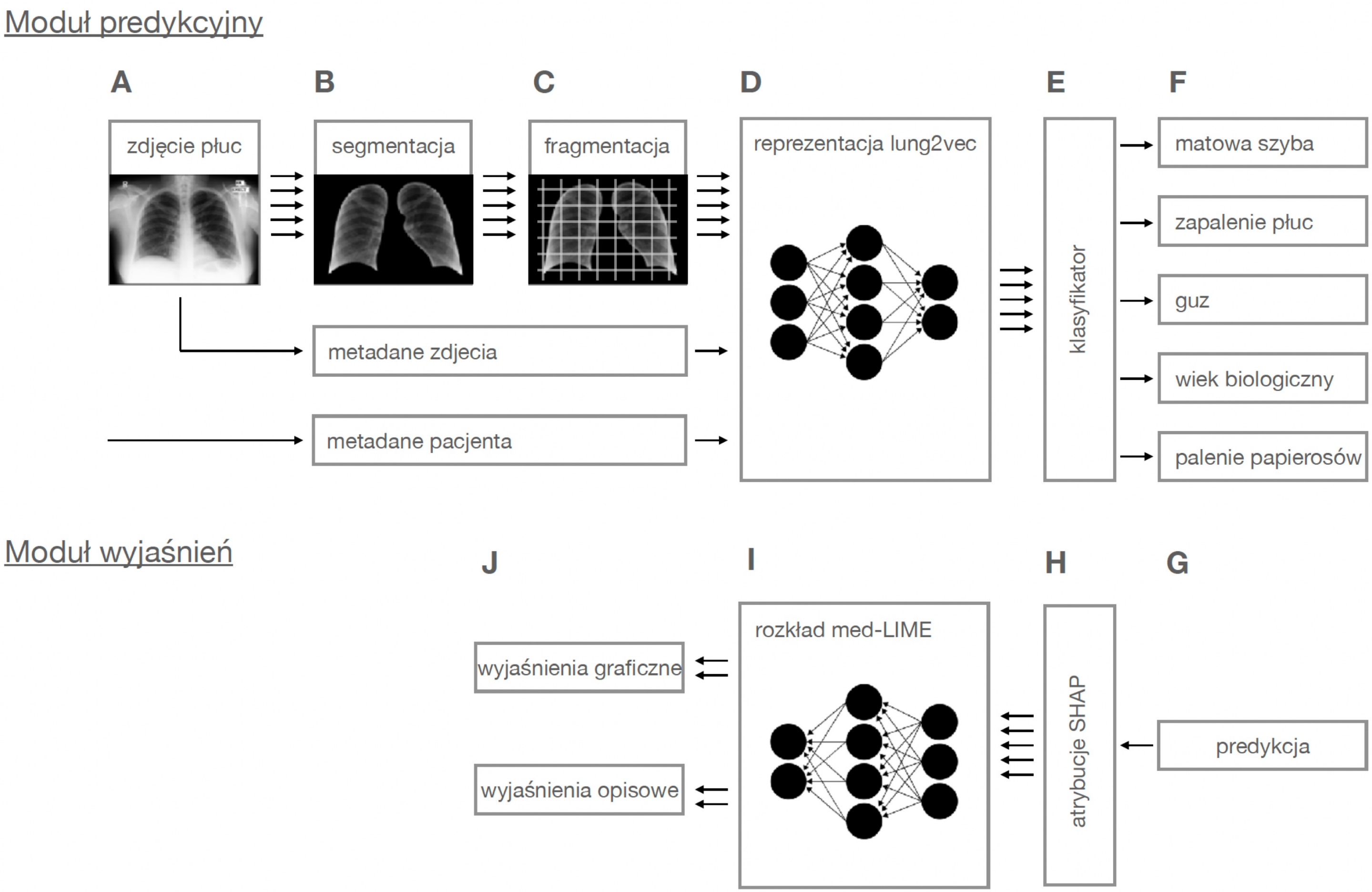


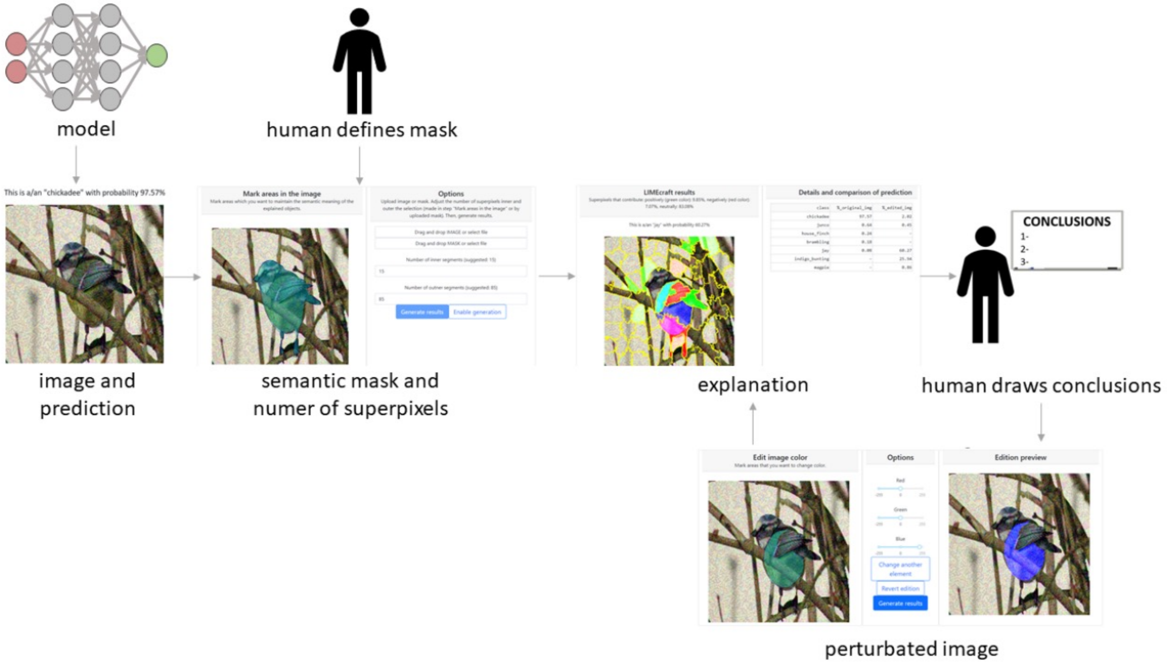
Computer Science > Computer Vision and Pattern Recognition

[Submitted on 15 Nov 2021 (v1), last revised 30 Apr 2022 (this version, v2)]

LIMEcraft: Handcrafted superpixel selection and inspection for Visual eXplanations

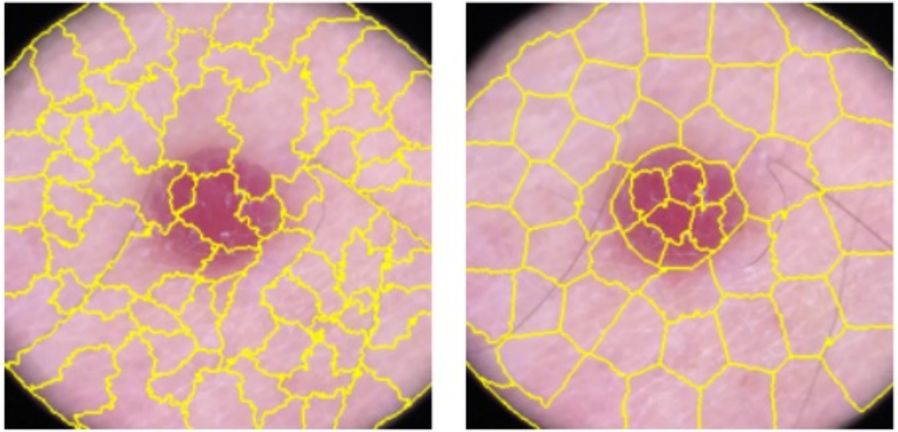
Weronika Hryniewska, Adrianna Grudzień, Przemysław Biecek

The increased interest in deep learning applications, and their hard-to-detect biases result in the need to validate and explain complex models. However, current explanation methods are limited as far as both the explanation of the reasoning process and prediction results are concerned. They usually only show the location in the
lack of possibility to interact with explanations makes it difficult to verify an
creates a significant risk when using the model. The risk is compounded by
the semantic meaning of the explained objects. To escape from the trap of s
tool and a process called LIMEcraft. LIMEcraft enhances the process of expla
semantically consistent areas and thoroughly examine the prediction for the
Experiments on several models show that our tool improves model safety by
may indicate model bias. The code is available at: this http URL



Subjects: **Computer Vision and Pattern Recognition (cs.CV)**; Machine Learning (cs.LG)
Cite as: arXiv:2111.08094 **[cs.CV]**
(or arXiv:2111.08094v2 **[cs.CV]** for this version)
https://doi.org/10.48550/arXiv.2111.08094

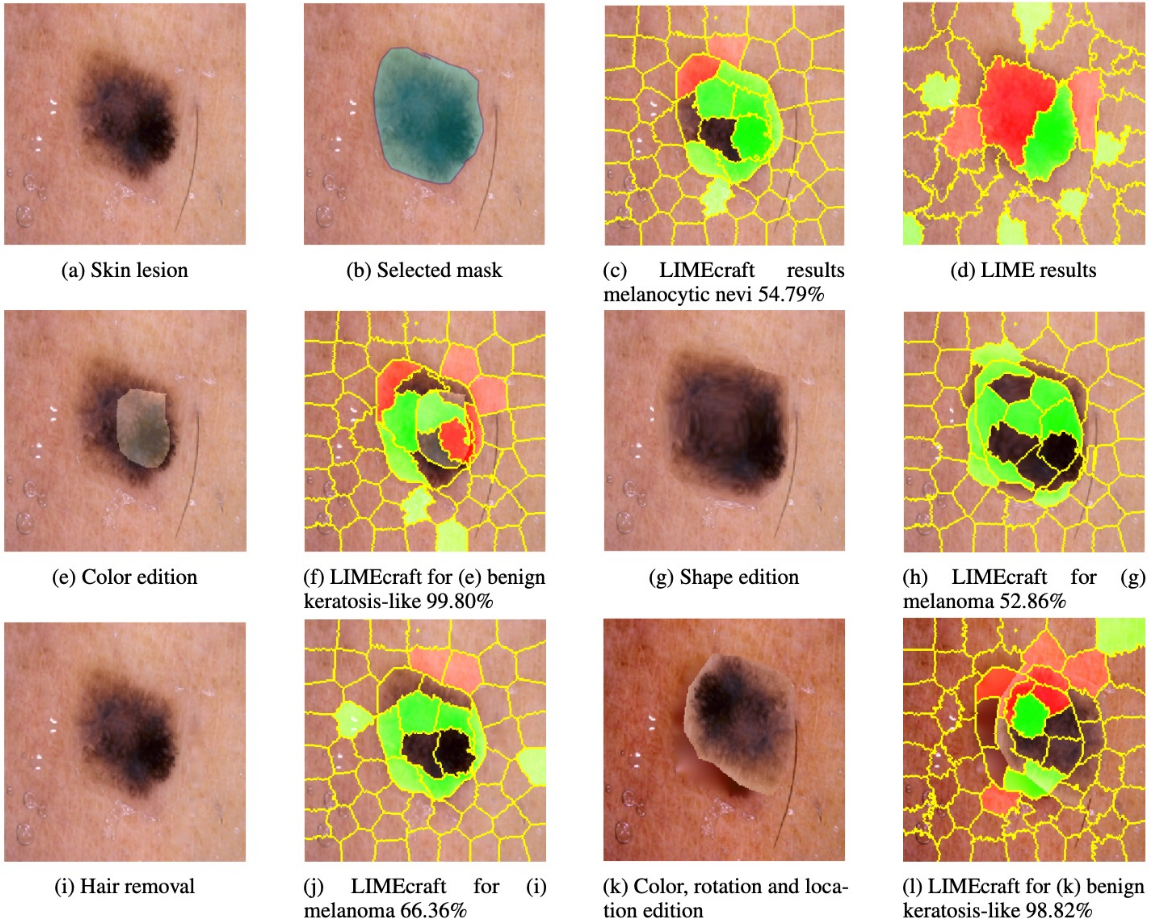
Explain!



Try this yourself
https://limecraft.mi2.ai/

Explain!

MI × LUNGS



(a) Skin lesion

(b) Selected mask

(c) LIMEcraft results melanocytic nevi 54.79%

(d) LIME results

(e) Color edition

(f) LIMEcraft for (e) benign keratosis-like 99.80%

(g) Shape edition

(h) LIMEcraft for (g) melanoma 52.86%

(i) Hair removal

(j) LIMEcraft for (i) melanoma 66.36%

(k) Color, rotation and location edition

(l) LIMEcraft for (k) benign keratosis-like 98.82%

Try this yourself
https://limecraft.mi2.ai/

Important but overlooked aspects

To build a good AI system it is needed to take care of:

- high quality **data**
- methods of reducing undesired **bias**
- methods of exploring and **explaining** models
- many other topics that I will not talk about today

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- Solutions
- Trainings

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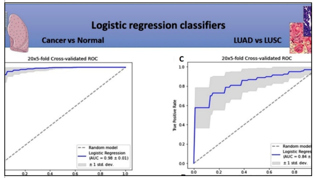
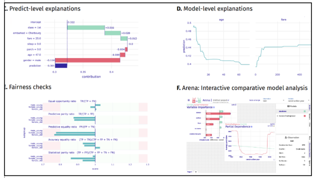
- Teaching
- Beta Bit
- ResponsibleML Blog

↘ Papers



A Signature of 14 Long Non-Coding RNAs (lncRNAs) as a Step towards Precision Diagnosis for NSCLC↗

Anetta Sulewska, Jacek Niklinski, Radoslaw Charkiewicz, Piotr Karabowicz, Przemyslaw Biecek, Hubert Baniecki, Oksana Kowalczuk, Miroslaw Kozlowski, Patrycja Modzelewska, Piotr Majewski et al.



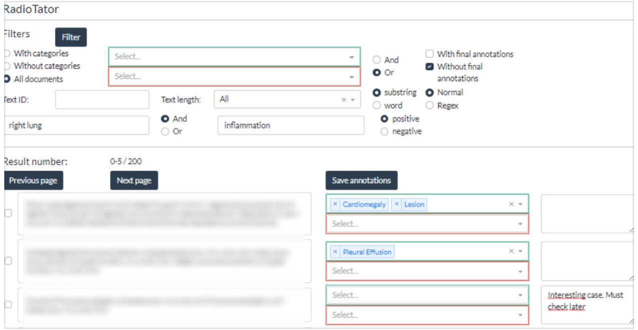
dalex: Responsible Machine Learning with Interactive Explainability and Fairness in Python↗

Hubert Baniecki, Wojciech Kretowicz, Piotr Piątyszek, Jakub Wiśniewski, Przemyslaw Biecek

Journal of Machine Learning Research (2021)

https://www.mi2.ai/

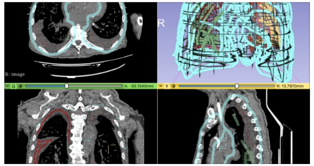
https://medium.com/responsibleml



RadioTator: A Tailored Tool for Rapid Medical Text Annotation

Creating an annotation app for text data to use for radiologists.

Jakub Wiśniewski
Jun 14 · 4 min read



Radiologists' nightmare— segmentation masks

This blog is the second in our xLungs series about the Responsible Artificial Intelligence for Lung Diseases project. You can check out…

Paulina Tomaszewska
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Towards the largest database of Polish lung medical images

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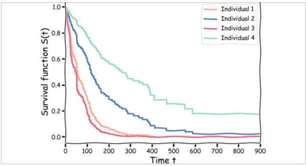

Responsible Machine Learning for Survival Analysis

A brief introduction to survival analysis and the use of machine learning models in this area

Mateusz Krzyziński
Jan 19 · 9 min read

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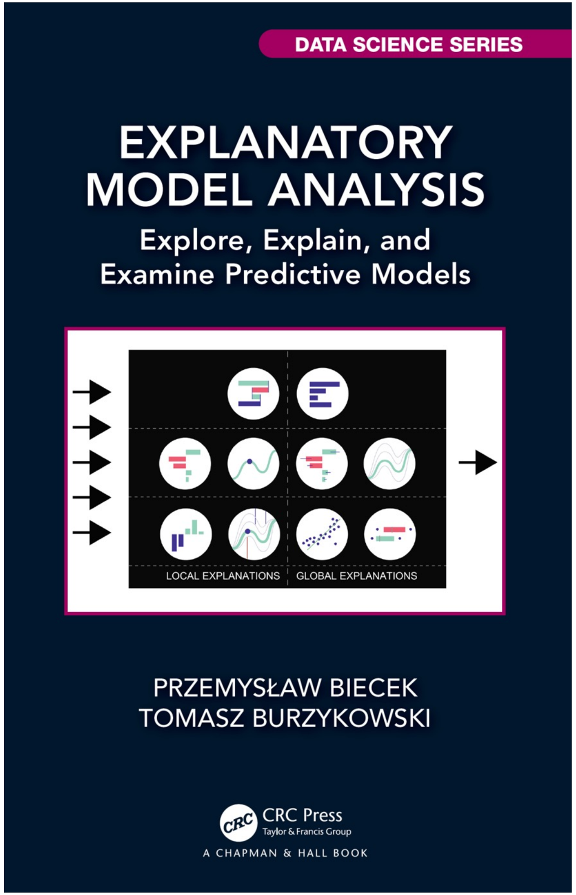

https://ema.drwhy.ai/

https://github.com/BetaAndBit/RML