Fairness, Explainability & Robustness in Machine Learning

EEIP Lecture Series - 3rd November 2020

Celia Cintas

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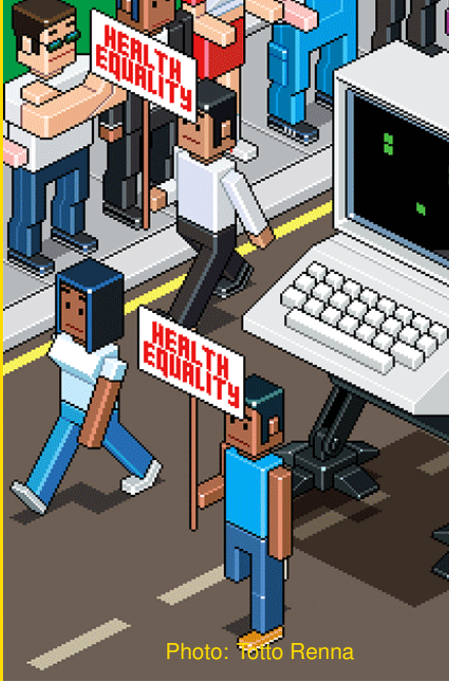

Photo: Tolfo Renna

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Why is it important?

ML may seem like an **objective** solution

An algorithm is shown a large amount of representative data to learn from. It is important to know that any data we give to the ML model **describes the choices that have already been made in society**.

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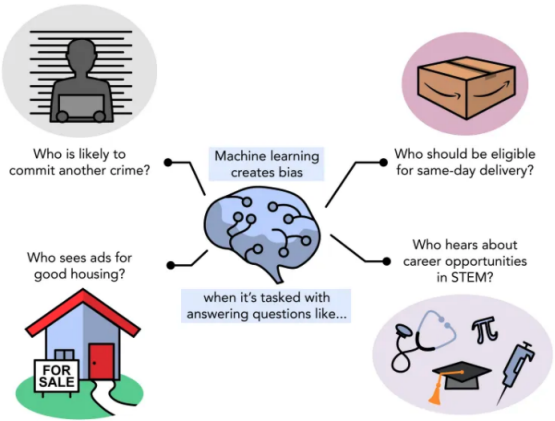
Why is it important? (Cont.)



MOTHERBOARD
TECH BY VICE

Google's Sentiment Analyzer Thinks Being Gay Is Bad

Amazon working to address racial disparity in same-day delivery service

By T.C. Sottek | May 8, 2016, 11:38am EDT
Source Bloomberg and Bloomberg

MIT Technology Review

Facebook's ad-serving algorithm discriminates by gender and race

Homes for sale are shown to a higher fraction of white users

The fraction of white users in the ad's audience

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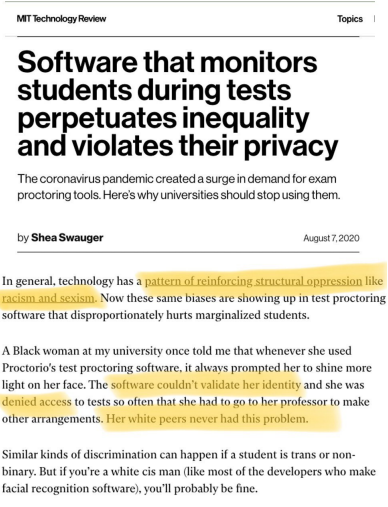
Figure: Nicholas Lue

Inequality in solutions during the COVID-19 crisis: Education



MIT Technology Review Topics

Software that monitors students during tests perpetuates inequality and violates their privacy

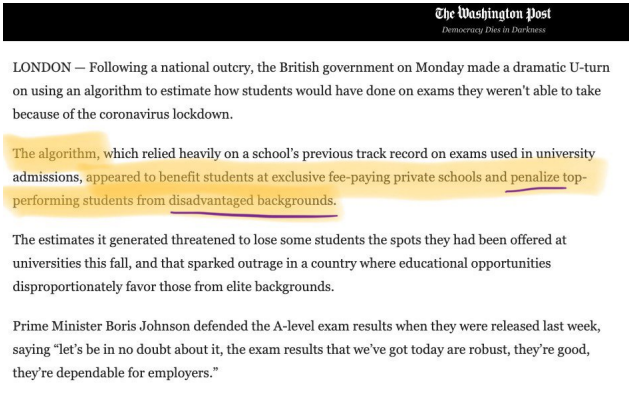
The coronavirus pandemic created a surge in demand for exam proctoring tools. Here's why universities should stop using them.

by **Shea Swauger** August 7, 2020

In general, technology has a pattern of reinforcing structural oppression like racism and sexism. Now these same biases are showing up in test proctoring software that disproportionately hurts marginalized students.

A Black woman at my university once told me that whenever she used Proctorio's test proctoring software, it always prompted her to shine more light on her face. The software couldn't validate her identity and she was denied access to tests so often that she had to go to her professor to make other arrangements. Her white peers never had this problem.

Similar kinds of discrimination can happen if a student is trans or non-binary. But if you're a white cis man (like most of the developers who make facial recognition software), you'll probably be fine.



The Washington Post
Democracy Dies in Darkness

LONDON — Following a national outcry, the British government on Monday made a dramatic U-turn on using an algorithm to estimate how students would have done on exams they weren't able to take because of the coronavirus lockdown.

The algorithm, which relied heavily on a school's previous track record on exams used in university admissions, appeared to benefit students at exclusive fee-paying private schools and penalize top-performing students from disadvantaged backgrounds.

The estimates it generated threatened to lose some students the spots they had been offered at universities this fall, and that sparked outrage in a country where educational opportunities disproportionately favor those from elite backgrounds.

Prime Minister Boris Johnson defended the A-level exam results when they were released last week, saying "let's be in no doubt about it, the exam results that we've got today are robust, they're good, they're dependable for employers."

Inequality in solutions during the COVID-19 crisis: Health

Healthcare IT News

AI bias may worsen COVID-19 health disparities for people of color

A new article in the Journal of the American Medical Informatics Association points to the dissemination of "under-developed and potentially biased models" in response to the novel coronavirus.

Stanford SOCIAL INNOVATION Review

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Technology

The Problem With COVID-19 Artificial Intelligence Solutions and How to Fix Them

NEWS & FEATURES

Artificial Intelligence, Health Disparities, and Covid-19

How racially biased is AI medicine? Experts are asking if biased algorithms worsen Covid-19's toll on Black Americans.

Visual: FG Trade / Getty Images

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Why is it hard to fix?

Unknown sources The introduction of bias isn't always obvious during a model's construction.

Missing ethics design Many of the standard practices in deep learning are not designed with bias detection in mind.

The definitions of fairness It's also not clear what the absence of bias should look like.

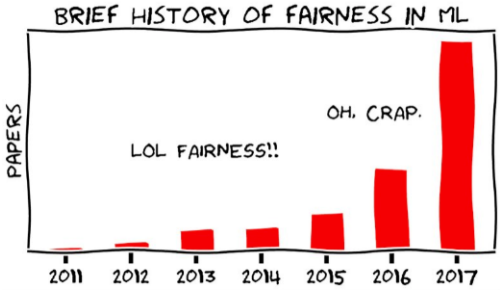

Figure: Moritz Hardt

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Source: MIT Review by Karen Hao

How & when can fairness be improved in our ML pipelines?

1. Detect and Report bias.
2. Mitigation techniques:
   - Pre-processing algorithms can be used if we can modify the training data.
   - We can use In-processing algorithms if we can change the learning procedure for a ML model.
   - If we need to treat the learned model as a black-box and cannot modify the training data or learning algorithm, we will need to use the Post-processing algorithms.
3. Continuous Pipeline Measurement. The probability distribution governing data can change over time, resulting in the training data distribution drifting away from the actual data distribution. Bias measurement and mitigation should be integrated into your continuous pipeline measurements.

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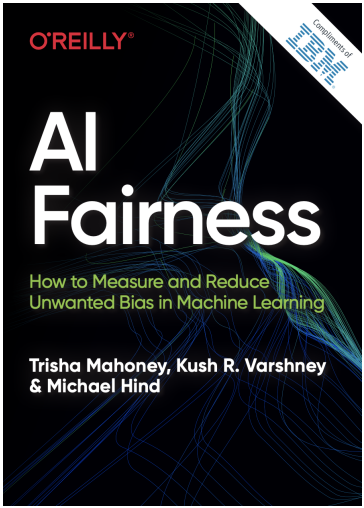
How & when can fairness be improved in our ML pipelines? (Cont.)

Pre-Processing Algorithms Mitigate bias in training data	In-Processing Algorithms Mitigate bias in classifiers	Post-Processing Algorithms Mitigate bias in predictions
Reweighing Modifies the weights of different training examples	**Adversarial Debiasing** Uses adversarial techniques to maximize accuracy and reduce evidence of protected attributes in predictions	**Reject Option Classification** Changes predictions from a classifier to make them more fair
Disparate Impact Remover Edits feature values to improve group fairness	**Prejudice Remover** Adds a discrimination-aware regularization term to the learning objective	**Calibrated Equalized Odds** Optimizes over calibrated classifier score outputs that lead to fair output labels
Optimized Preprocessing Modifies training data features and labels	**Meta Fair Classifier** Takes the fairness metric as part of the input and returns a classifier optimized for the metric	**Equalized Odds** Modifies the predicted label using an optimization scheme to make predictions more fair
Learning Fair Representations Learns fair respresentations by obfuscating information about protected attributes		



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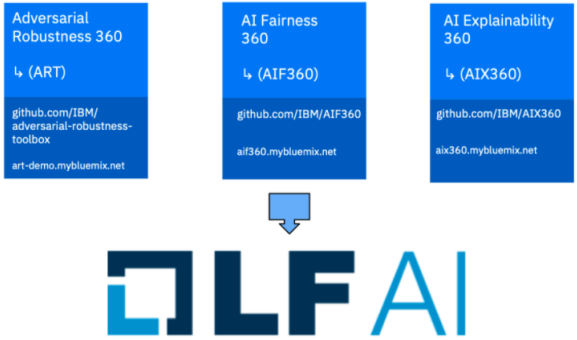
How & when can fairness be improved in our ML pipelines? (Cont.)



1. **AI Fairness 360** https://aif360.mybluemix.net/ examine, report, and mitigate discrimination and bias in machine learning.
2. **AI Explainability 360** https://aix360.mybluemix.net/ algorithms that span the different ways of explaining along with proxy explainability metrics.
3. **Adversarial Robustness Toolbox (ART)** https://art-demo.mybluemix.net/ provides tools to defend and evaluate ML models against adversarial threats.

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Properties that we need to asses in our ML solutions

Fairness ensures that a model's predictions do not unethically discriminate **unprivileged groups**.

Robustness defines expectations for how an ML model will behave upon **deployment in the real world**.

Transparency & Explainability tackles the question of **how** an ML model makes its predictions.

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Current Research Projects

IJCAI-PRICAI YOKOHAMA 2020

Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence (IJCAI-20)

Detecting Adversarial Attacks via Subset Scanning of Autoencoder Activations and Reconstruction Error

Celia Cintas[1*], Skyler Speakman[1*], Victor Akinwande[1], William Ogallo[1], Komminist Weldemariam[1], Srihari Sridharan[1] and Edward McFowland[2]
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MICCAI 2020 Lima PERU

Estimating Skin Tone and Effects on Classification Performance in Dermatology Datasets

Newton M. Kinyanjui,[1,4] Timothy Odonga,[1,4] Celia Cintas,[1] Noel C. F. Codella,[2] Rameswar Panda,[3] Prasanna Sattigeri,[2] and Kush R. Varshney[1,2]
IBM Research, [1]Nairobi, Kenya. [2]Yorktown Heights, NY, USA. [3]Cambridge, MA, USA
[4]Carnegie Mellon University Africa, Kigali, Rwanda

PRESERVATION OF ANOMALOUS SUBGROUPS ON VARIATIONAL AUTOENCODER TRANSFORMED DATA

ICASSP2020 Barcelona

Samuel C. Maina[1] *Reginald E. Bryant*[1] *William O. Ogallo*[1]
Kush R. Varshney[1] *Skyler Speakman*[1] *Celia Cintas*[1]
Aisha Walcott-Bryant [1] *Robert-Florian Samoilescu*[1,2] *Komminist Weldemariam*[1]

[1] IBM Research, Nairobi, Kenya
[2]Politehnica University of Bucharest, Bucharest, Romania

1. Improving existing ML techniques to address global health challenges in developing countries. [CRA+20, DCOWB]
2. Leveraging statistical methods in the space of neural networks' activations to detect anomalies and provide robustness to trained models [CSA+20].
3. Investigating how to ensure that ML models are fair, robust and reliable for everyone [KOC+20].

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Disparities in ML & Dermatology

1. Are standard **dermatology image datasets** used in ML tasks **biased with respect to skin tone**? Can we quantify this?
2. If so, does the dataset bias lead to **unequal performance** of downstream disease classification?

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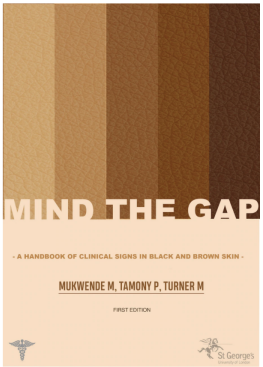
Disparities in Dermatology

- In the African American population, melanoma is often diagnosed at an advanced stage with deeper tumors [MSL+17, WEK+11].
- Five year survival rates for Acral Lentiginous Melanoma (ALM) is 82.6% in caucasian population, but only 77.2% in African American patients. [MCH15].
- The paucity of images of skin manifestations in patients with darker skin is problematic, because it may make identification of COVID-19 presenting with cutaneous manifestations more difficult for both dermatologists and the public. [LJZ+20]
- Dermatologists started an international registry to catalog examples of skin manifestations of COVID-19. The registry compiled more than 700 cases, but only 34 and 14 cases respectively for patients with Hispanic and African ancestry. [Rab20]



The cover of the "Mind the Gap" handbook, written by Malone Mukwende, with two of his lecturers, Peter Tamony and Margot Turner.

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Machine Learning & Dermatology

- Skin disease diagnosis using machine learning
  1. Benchmark model for melanoma diagnosis outperforms trained dermatologists [CNP+16]
  2. ISIC challenges (https://www.isic-archive.com/)
- Predictive inequity in computer vision with respect to skin type
  1. Automated face image analysis for gender classification [BG18]
  2. Pedestrian detection systems [WHM19]

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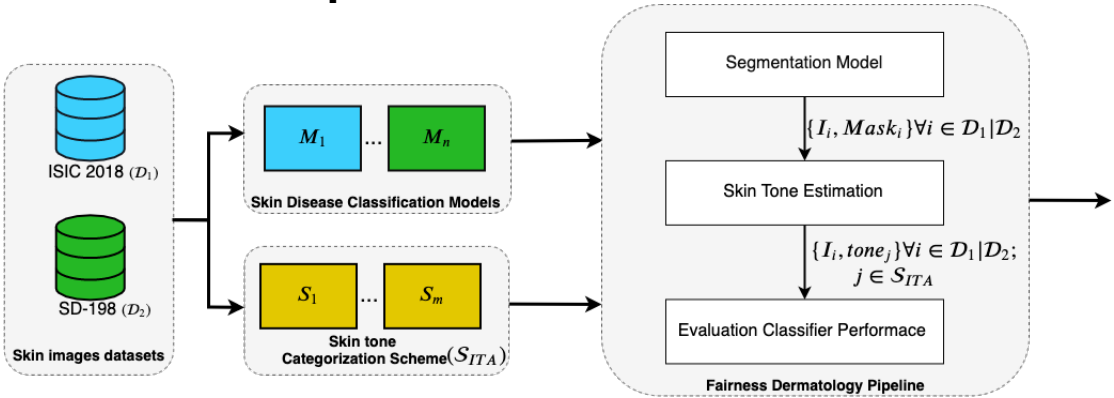
Overview : Proposed Framework



Kinyanjui, et al. "Estimating skin tone and effects on classification performance in dermatology datasets."MICCAI 2020 [KOC+20].

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Sensitive Content Warning

Skin Disease Graphical Content Warning

Note that we will show **skin disease examples** that could be **sensitive** or **triggering** to some viewers. We notice this, so viewers can prepare themselves to adequately engage or, if necessary, disengage for their own well-being.

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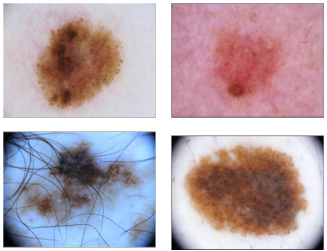
Datasets

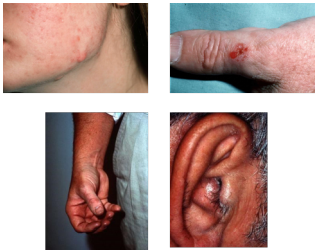
ISIC 2018

- 10015 dermoscopic images
- 7 disease classes
- 2594 images with ground truth segmentation masks for diseased area



SD-198

- 6548 clinical images
- 198 disease classes
- No segmentation data



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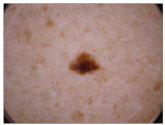
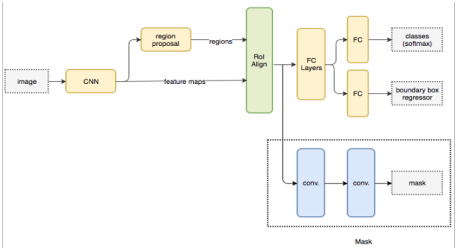
Segmentation to Obtain Non-Diseased Region

1. Finetune Mask R-CNN model ([HGDG17])
   - Adjust pretrained classifier with a FastRCNNPredictor with 2 classes (background and mask)
   - Adjust mask predictor with new MaskRCNNPredictor with 2 classes and 512 hidden neurons
2. Further apply thresholding techniques on predicted grayscale mask including contour extraction for ISIC2018 and grid search for optimal binary thresholding for SD-136





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Skin Tone Metric of Non-Diseased Region

1. Given non-diseased pixels, characterize them with a skin tone metric
   1. Use individual typology angle (ITA) [WWdPR15], Highly correlated with melanin index
   2. $\text{ITA} = \tan^{-1}\left(\frac{L-50}{b}\right) \times \frac{180}{\pi}$ Where L is luminance and b quantifies amount of yellow.
   3. Use pixels with L and b values within 1 standard deviation to deal with outliers.
2. Bin into categories [CSD+15]

ITA Range	Skin Tone Category	Abbreviation
ITA $> 55^\circ$	Very Light	very_lt
$48^\circ <$ ITA $\leq 55^\circ$	Light 2	lt2
$41^\circ <$ ITA $\leq 48^\circ$	Light 1	lt1
$34.5^\circ <$ ITA $\leq 41^\circ$	Intermediate 2	int2
$28^\circ <$ ITA $\leq 34.5^\circ$	Intermediate 1	int1
$19^\circ <$ ITA $\leq 28^\circ$	Tanned 2	tan2
$10^\circ <$ ITA $\leq 19^\circ$	Tanned 1	tan1
ITA $\leq 10^\circ$	Dark	dark

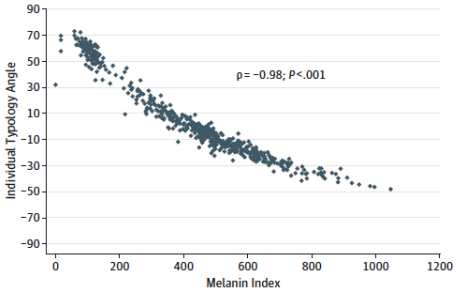

Figure from [WWdPR15].

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Classification of Skin Disease

We replicated state-of-the-art skin disease classification neural networks:

1. Finetune Densenet 201 model pretrained on ImageNet [HLVDMW17].
2. Regularization methods: Dropout and early stopping.

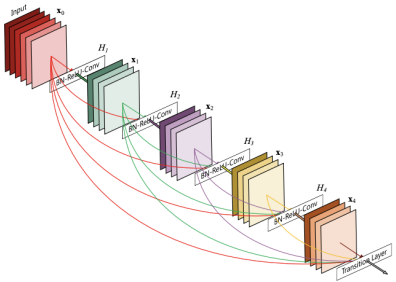

Figure from [HLVDMW17]

Overall accuracy on validation data

- ISIC2018: balanced accuracy 0.884 (benchmark model 0.885)
- SD-136: accuracy score 0.567 (benchmark model 0.52)

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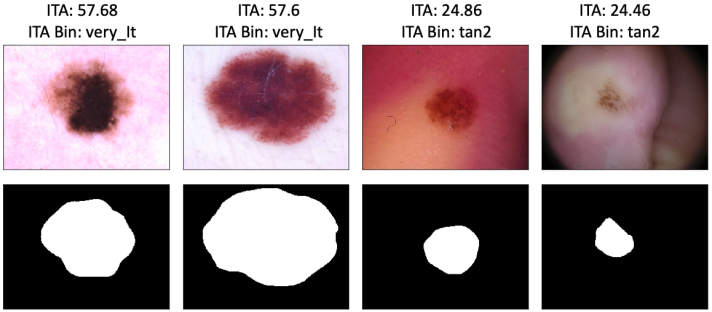
Results

Metrics for segmentation on ISIC 2018

The Mask R-CNN model yields an accuracy of **0.956**, a false negative rate of **0.024**, and a mean absolute error in ITA computation of **0.428** degrees. [KOC+20]



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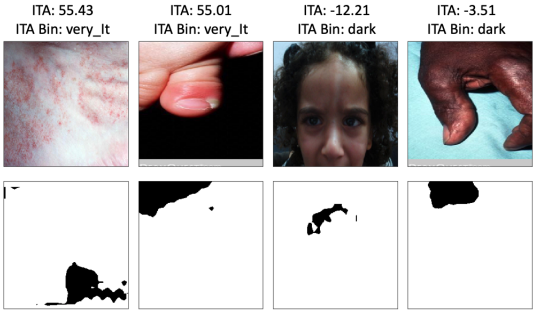
Results (Cont.)

Metrics for segmentation on SD-136

The segmentation model on the SD-136 dataset yield an accuracy of **0.802**, a false negative rate of **0.076**, and a mean absolute error in ITA computation of **3.572** degrees. [KOC+20]



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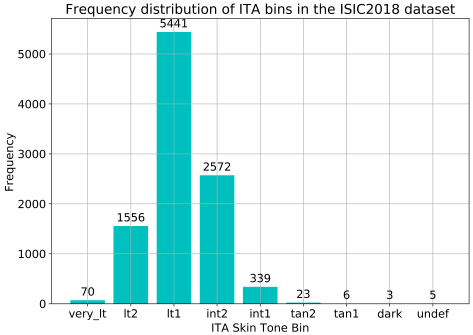
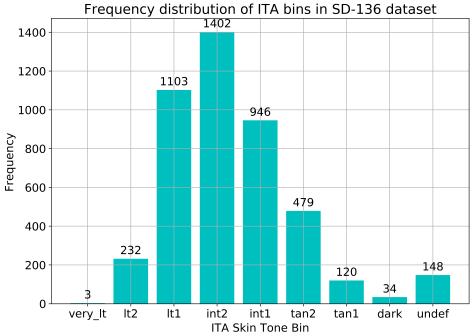
Results (Cont.)

Skin Tone Distribution

There is underrepresentation of darker skin tones in both datasets





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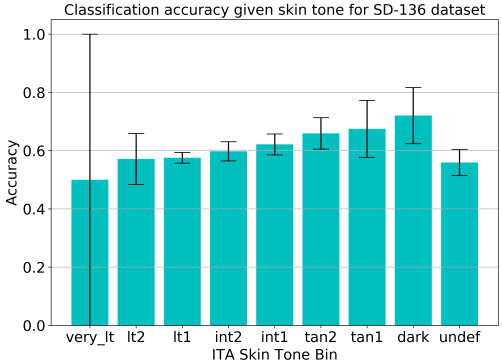
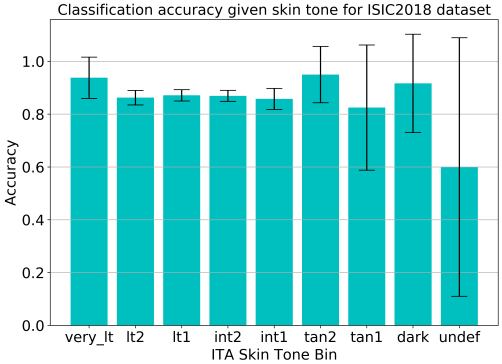
Results (cont.)

Accuracy by Skin Tone

There is no statistically significant pattern of unequal performance by skin tone

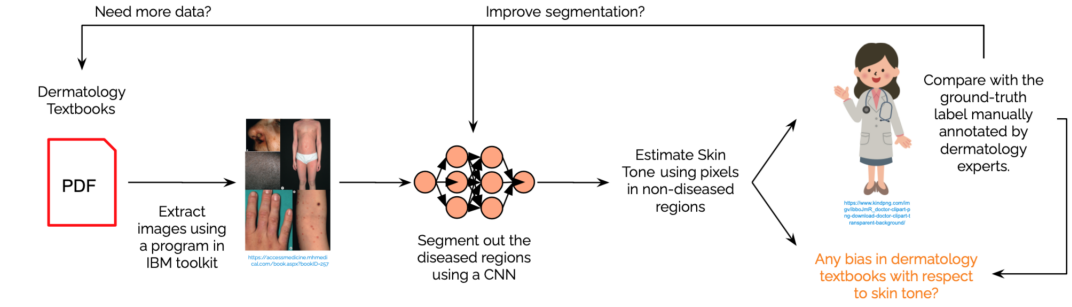




Extensions

Automatic report of skin tone distributions

Kim et al. are currently working on extending the current segmentation and classification models to work on dermatology textbooks and academic paper images.



Further experiments & Open Questions on Fair Dermatology

1. Experiments around stratification of skin tone by disease.
2. How a fair distribution looks like in this case?
3. How can we improve the segmentation process across all skin tones?
4. How can we collaborate with dermatologists across the continent to avoid having only US-centric sources in dermatology?

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Subset Scanning for Out Of Distribution Detection

1. Can we detect when a sample looks **odd or new** to our ML model?
2. Can we detect if a sample is **generated** or **modified**?
3. Can we know **what** makes a sample odd or fake?

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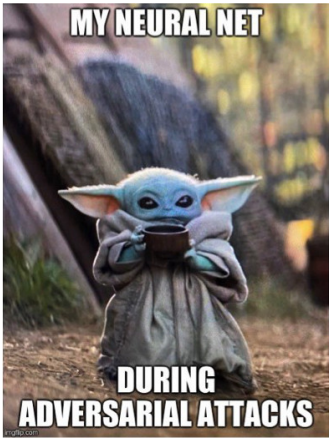
Why is important to detect adversarial attacks?

Reliably detecting attacks in a given set of inputs is of high practical relevance due to the vulnerability of neural networks to adversarial examples. These altered inputs create a security risk in applications with real-world consequences, such as self-driving cars, robotics and financial services.



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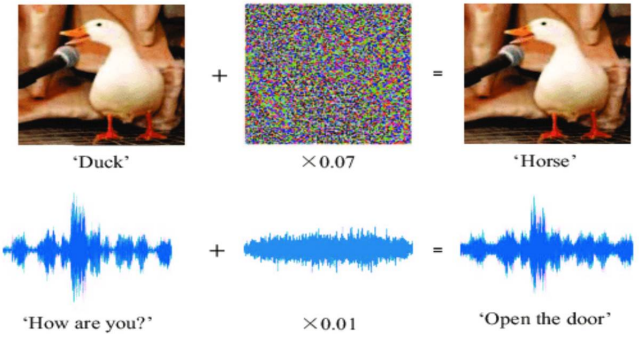
What is an Adversarial Attack?

white-box an attacker has complete access to the model, including its structure and trained weights. E.g. Basic Iterative Method (BIM) [KGB16], Fast Gradient Signal Method (FGSM) [GSS15], DeepFool (DF) [MDFF16].

black-box an attacker can only access the outputs of the target model. (e.g HopSkipJumpAttack [CJW19]).



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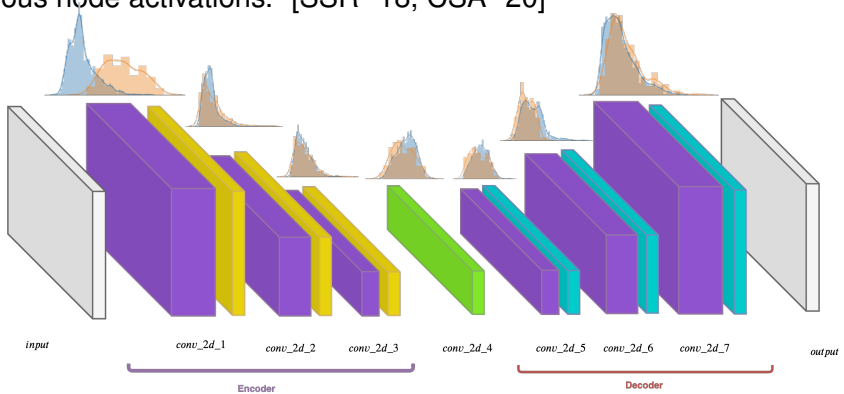
Picture: https://whataftercollege.com/machine-learning/adversarial-attack-machine-learning/

Subset Scan for Anomalous Pattern Detection

We propose an unsupervised method for detecting adversarial attacks in inner layers of autoencoder (AE) networks by maximizing a non-parametric measure of anomalous node activations. [SSR+18, CSA+20]



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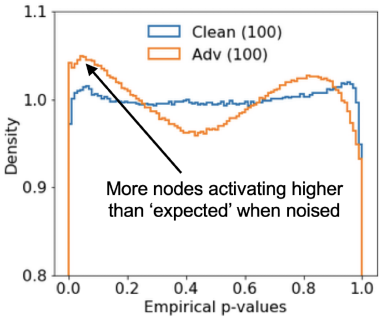
Subset Scanning for Anomalous Pattern Detection (Cont.)



Assumption

Activations from adversarial images have a different distribution of p-values than benign/clean samples.

p-value is the proportion of background activations (H_0), drawn from the same node for several clean samples, greater than the activation from a test sample.

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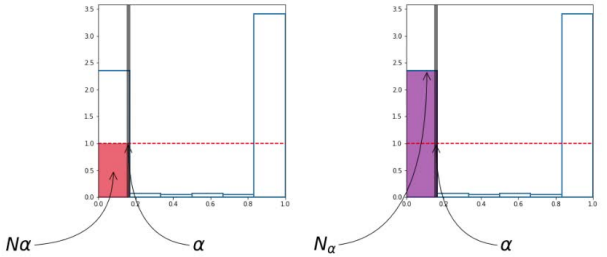
Subset Scanning for Anomalous Pattern Detection (Cont.)



$$\max_{\alpha} \varphi(\alpha, N_\alpha, N) = \frac{N_\alpha - N\alpha}{\sqrt{N}} \quad (1)$$

Where N_α is the number of p-values less than α
N is the number of p-values
α is the level of significance

How we score new images?

Scoring functions operate on an evaluation image in order to measure how much the p-values deviate from uniform.

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Subset Scanning for Anomalous Pattern Detection (Cont.)

Subset scanning (SS) treats the pattern detection problem as a search for the *most anomalous* subset of activations.

NPSS maximization

Scoring functions may be viewed as set functions that operate on subsets of nodes. We search for the highest scoring subset of nodes that maximize the deviance from uniform.

$$F(S) = \max_{\alpha} F_{\alpha}(S) = \max_{\alpha} \varphi(\alpha, N_{\alpha}(S), N(S)) \tag{2}$$

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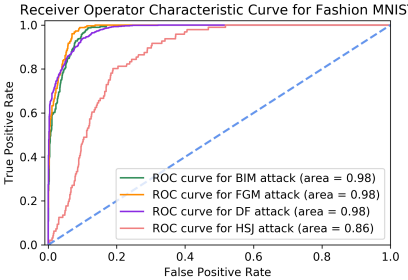
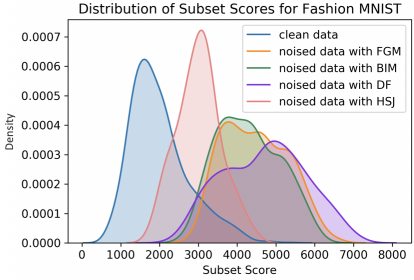
Results in Inner Layers





ROC curves & Distribution of subset scores

For each of the noised cases as compared to the scores from test sets containing all natural images for layer *Conv2d_1*. Distribution of subset scores for test sets of images over *Conv2d_1*. Clean images had lower scores than noised images.

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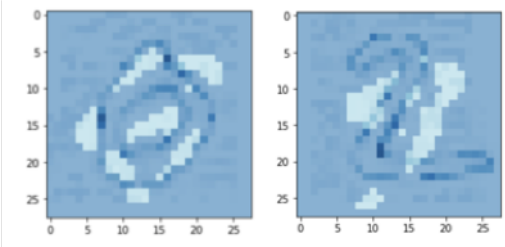
Results over the Reconstruction Error

The results over the RE depend on the AE performance. If an autoencoder's loss is high, it is more difficult to separate between clean and noised samples in the reconstruction space because the most anomalous subset of reconstructed pixels of a clean image may be higher due to chance.



Datasets	Attacks	Detection Power (AUROC)		
		Ours RE	Mean RE	One-SVM
F-MNIST	BIM	**0.698**	0.641	0.478
	FGSM	**0.672**	0.630	0.497
	DF	**0.599**	0.477	0.534
	HSJ	**0.956**	0.935	0.546
MNIST	BIM	**0.998**	0.751	0.624
	FGSM	**0.983**	0.725	0.624
	DF	**0.992**	0.574	0.637
	HSJ	**0.999**	0.619	0.537

Explainability

Subset Scanning over the reconstruction error space is an interesting technique to inspect **which pixels** of the reconstructed image belong to the **most anomalous subset**.

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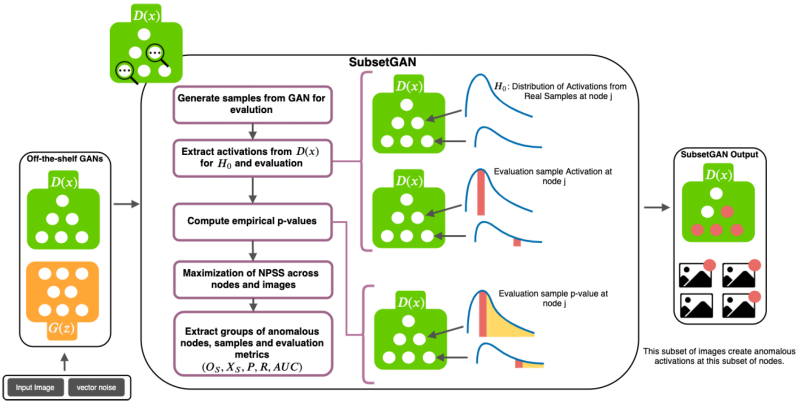
Fake Content Detection as an Anomalous Pattern Problem



Sample generation from PGGAN & StarGAN [KALL17, CCK+18].

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Further experiments & Open Questions on Robust detection of OOD

- Can we utilize the information from a subset of nodes to make models more **robust**?
- Can we **detect** when a **new class** appears at Inference time?
- Can we **inform how** a sample **is generated** with nodes visualization?

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My two cents :)

1. It is crucial that the groups that develop & research technological solutions for sectors such as education, health, etc., are interdisciplinary.
2. Researchers and developers have to be as diverse than their end users. -or more so
3. The operational constraints and limitations of production models must be clearly and explicitly define.
4. The models to be used in production must make explicit in which context they work and their limitations, be transparent, clarify what biases were evaluated and what are the mitigation techniques used.

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Interesting Resources and Materials

- Tutorials & Books
  1. Fairness in machine learning (NIPS 2017)
  2. 21 fairness definitions and their politics (FAT* 2018)
  3. Fairness and machine learning: Limitations and Opportunities (https://fairmlbook.org/) [BHN19]
- Lectures
  1. Berkeley CS 294: Fairness in machine learning (https://fairmlclass.github.io/)
  2. Cornell INFO 4270: Ethics and policy in data science
  3. Princeton COS 597E: Fairness in machine learning
- Conferences
  1. ACM Conference on Fairness, Accountability, and Transparency (ACM FAccT) (https://facctconference.org/)
- Initiatives and Communities
  1. MD4SG (http://md4sg.com/)
  2. Trustworthy ML (https://www.trustworthyml.org/)

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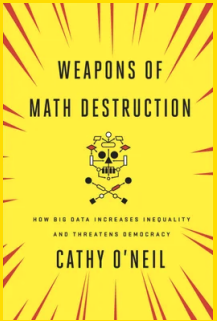
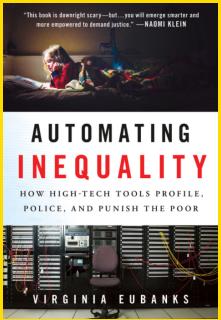
Gracias! Thanks! Asante!





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