

Lecture 3: Implementing AI in Healthcare (part 2)

Data Sciences Institute
Topics in Deep Learning
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- "We should stop training radiologists now. It's just completely obvious that within five years, deep learning is going to do better than radiologists."
 - [Geoff Hinton \(2016\)](#), the “godfather of AI”



'It's bad, it's really bad': Regina woman waits months for a breast biopsy amid backlog

Sask. Minister of Health confirms shortage of medical radiation technologists, specialized breast radiologists.

Oct 26, 2023



Imaging Technology News

[Minding the Gap: Strategies to Address the Growing Radiology Shortage](#)

This staffing issue is likely to continue for the next decade, creating even bigger challenges for many hospitals. In fact, the Association of...

Jul 13, 2023



Lecture Outline

- Bias (ethical)
- Bias (statistical)
- Types of bias
- Addressing bias
- Risk
- Generalization
- Best practices

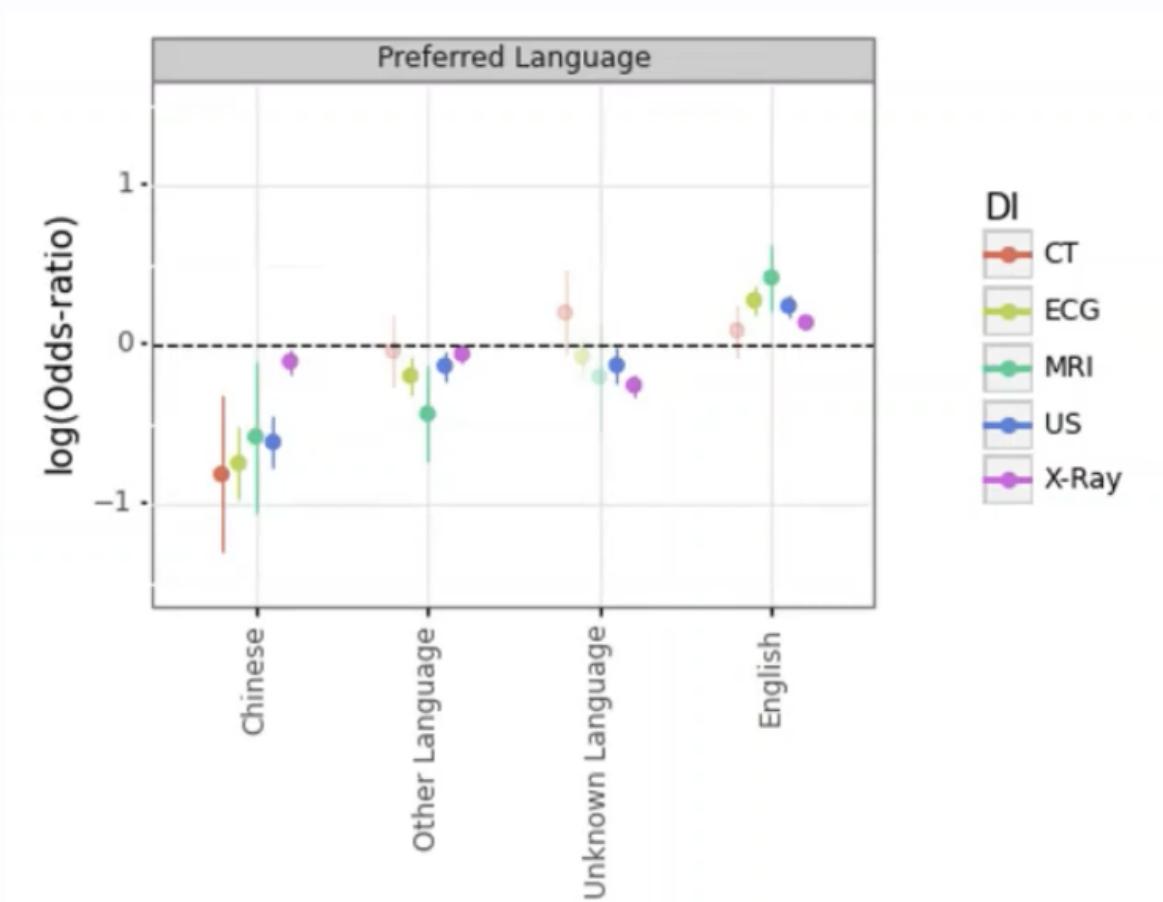
Introduction

- The integration of AI in healthcare has great potential for improving patient care, but it is not without challenges.
- This presentation will delve into key pitfalls: bias, risk, and generalization, associated with AI in healthcare.

Bias (ethical)

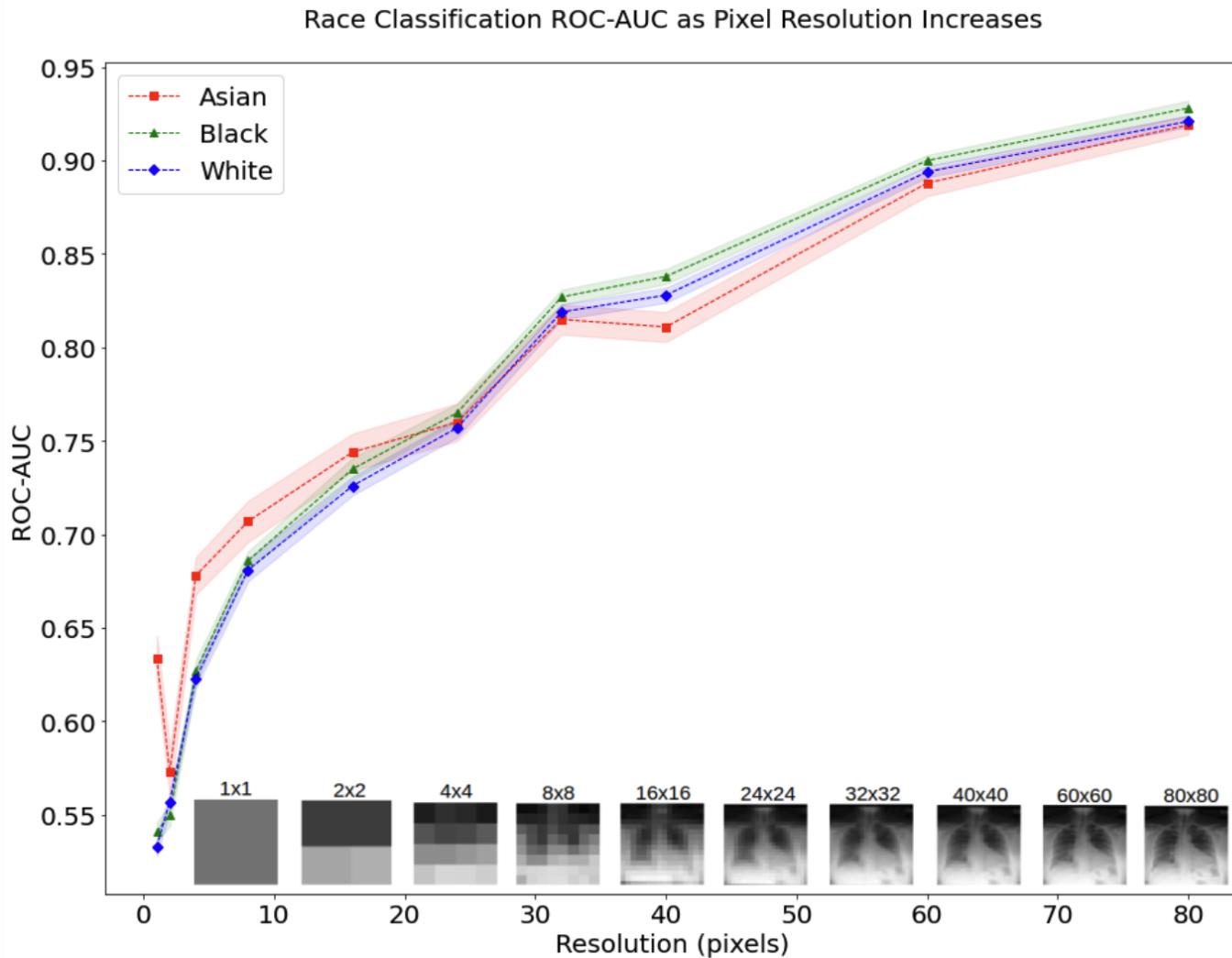
- Bias in AI refers to the systematic and unfair discrimination or favoritism in the outcomes produced by artificial intelligence systems, algorithms, or models.
- In healthcare it may lead to unequal access to healthcare, inaccurate diagnoses, or disparities in treatment recommendations based on various factors.

Bias is inherent in medical practice



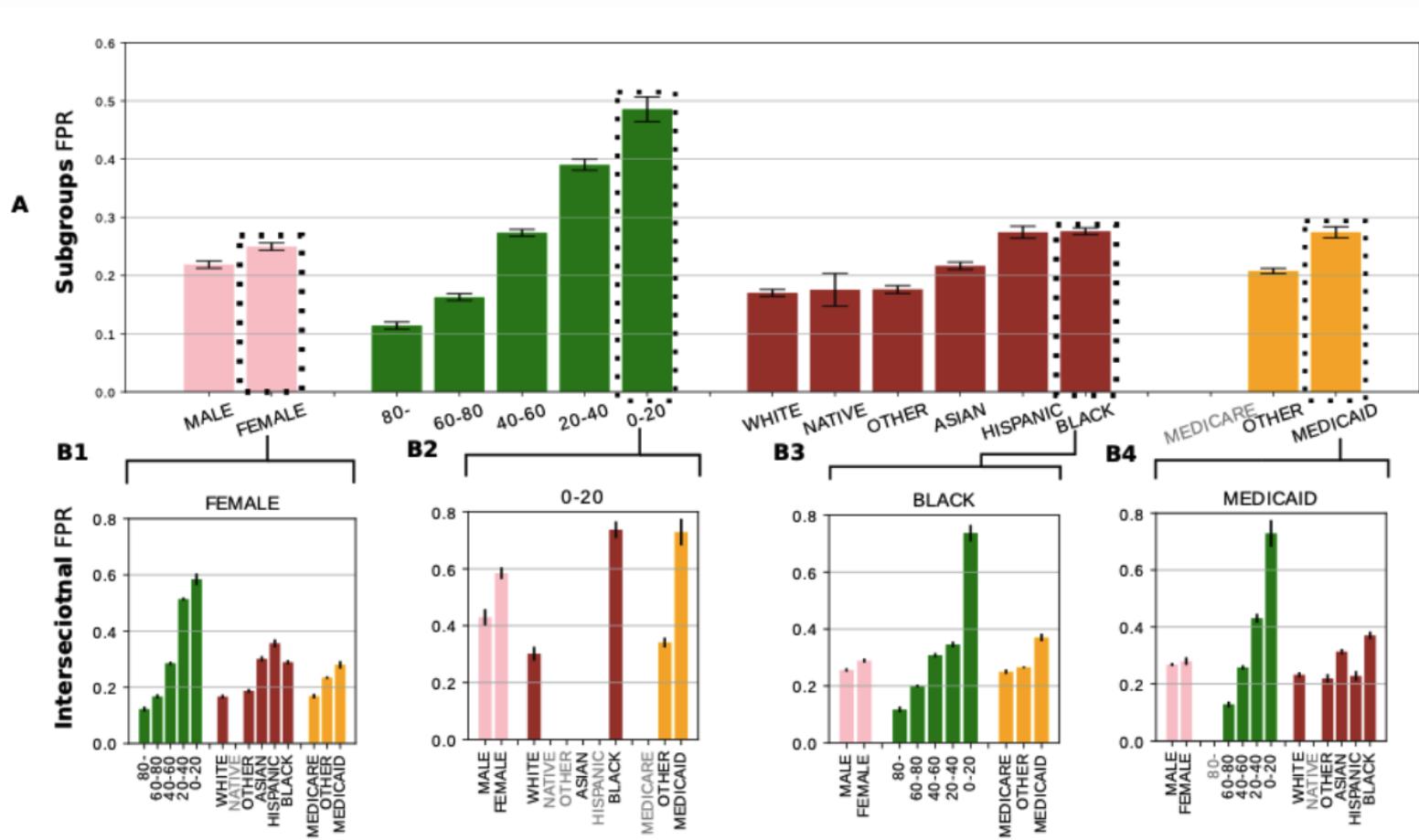
Source: Artificial Intelligence and Nursing - NPAO 2021

And is invisible to the human eye



Source: Gichoya et. al (2022)

Which means it will be inherent in model inference



Source: Zhang et. al (2023)

Which means it will be inherent in model inference

Prompt: [**RACE**] pt became belligerent and violent .
sent to [**TOKEN**] [**TOKEN**]

SciBERT: caucasian pt became belligerent and violent .
sent to hospital .
white pt became belligerent and violent . sent
to hospital .
african pt became belligerent and violent .
sent to prison .
african american pt became belligerent and
violent . sent to prison .
black pt became belligerent and violent . sent
to prison .

Token completion generated by SciBERT (see Zhang et. al (2020))

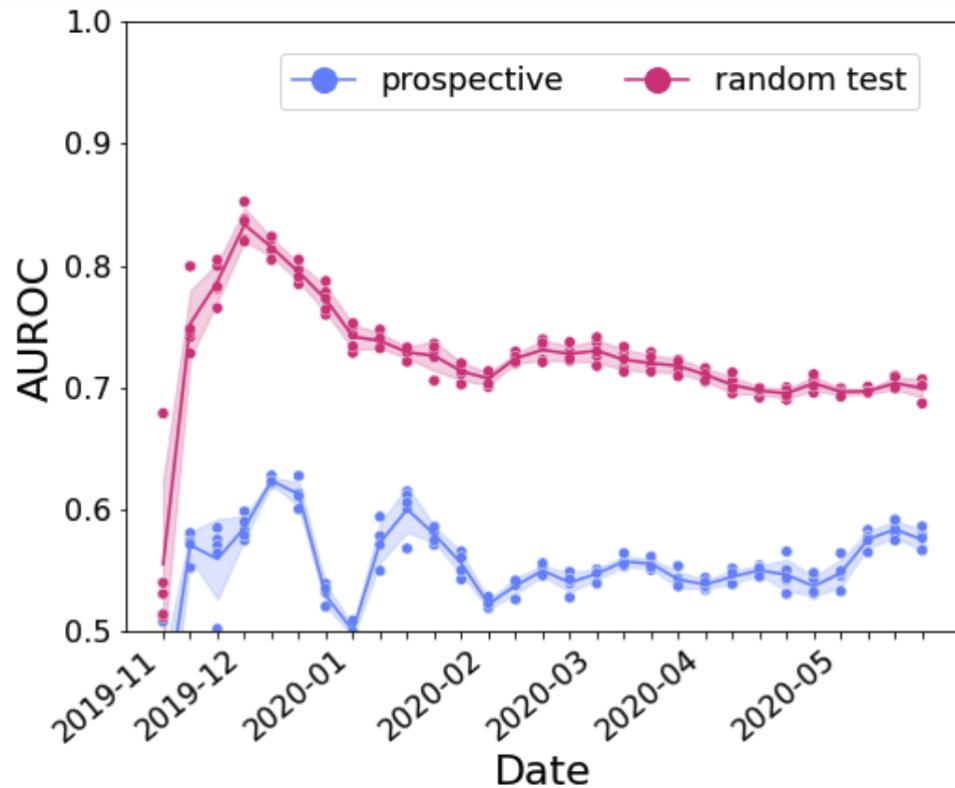
Bias (statistical)

Bigger is not always better

- If you wanted to know a proportion (e.g. % who will vote for a president, true positive rate, etc), do you want 400 truly random samples, or 2.3 million samples where there's a 0.5% bias against reporting for one group?
 - Answer: n=400 (source [Meng \(2018\)](#))
- Representativeness is key!

Test set structure

- It's very important to create a test set that (most) closely resembles prospective deployment



Test set structure

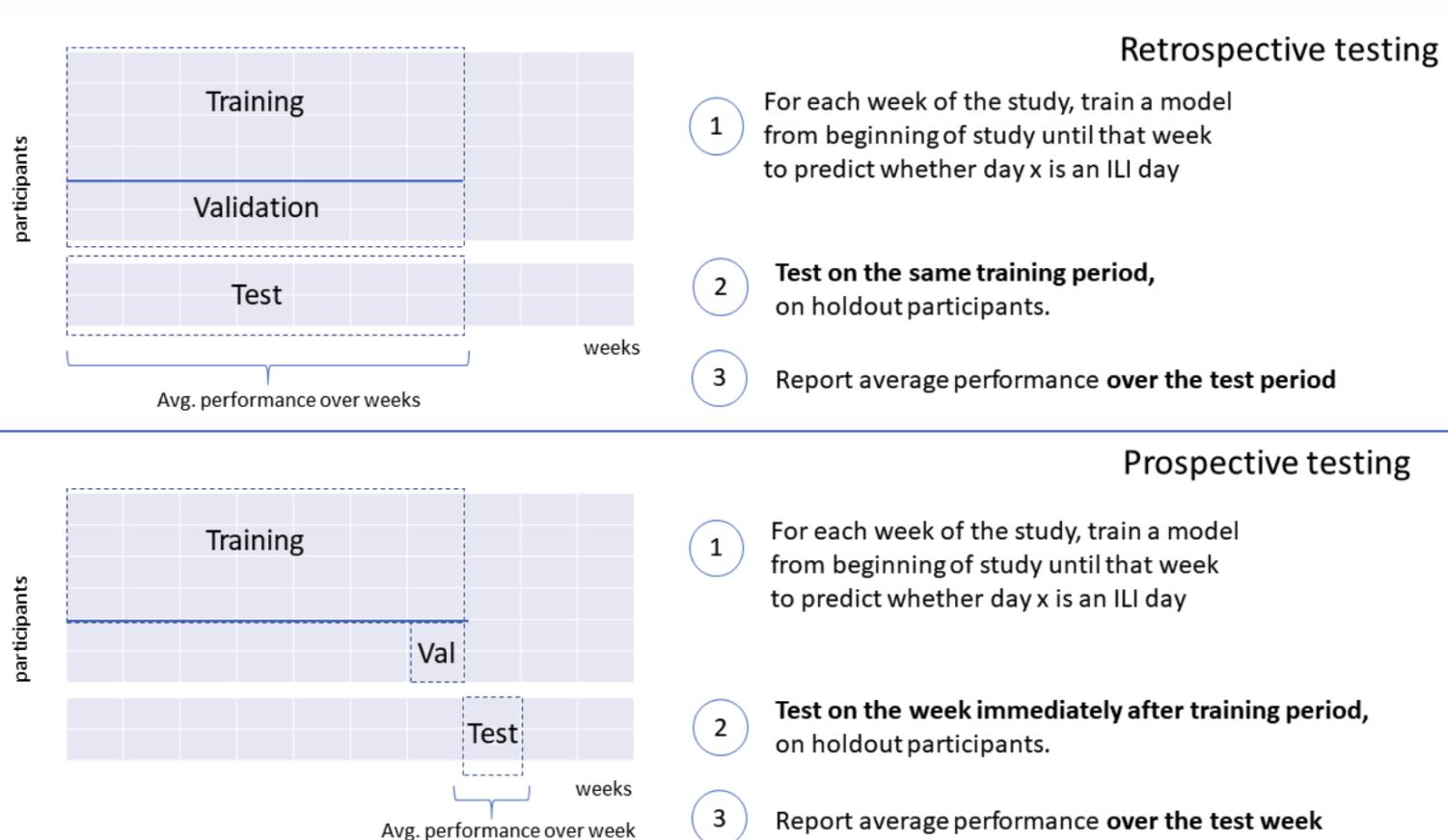


Figure S1. Retrospective vs. Prospective testing setup

Source: Nestor et. al (2021)

Breakout #1

Why would we expect prospective test set performance to be worse on average than a random split?

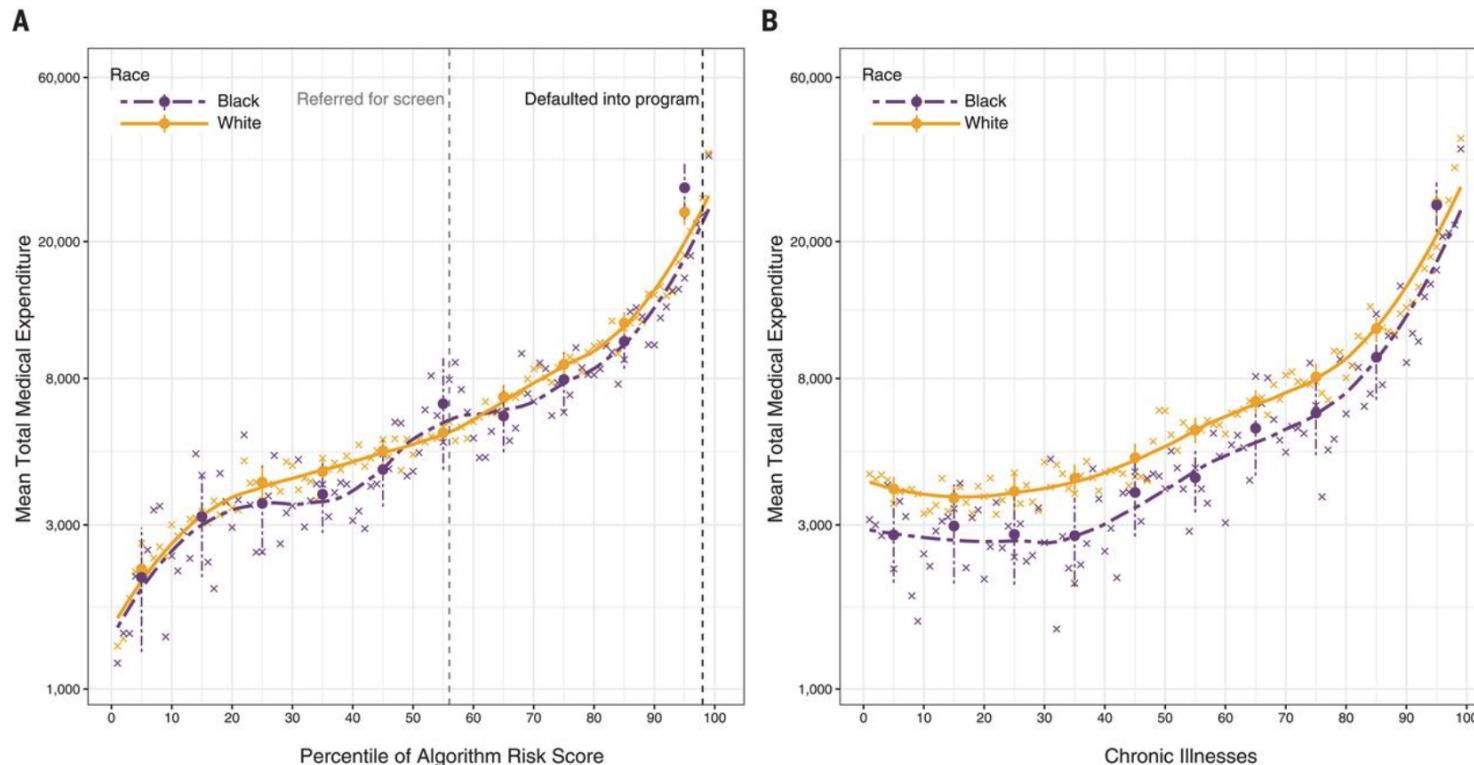
Types of Bias

Selection Bias

- Selection bias is associated with the manner in which the data used for training or evaluation is collected.
- It arises when the data collection process favors certain groups or circumstances over others.
- Selection bias can introduce systemic bias into the dataset (i.e. non-representativeness).

Labeling Bias

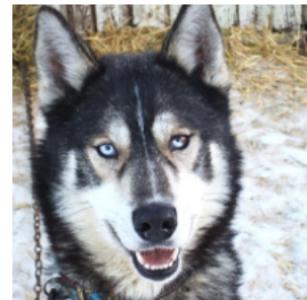
- Can arise when the labels assigned to training data reflect existing prejudices or stereotypes
- Can also occur during the annotation or labeling of data points.



Source: Obermeyer et. al (2019)

Algorithmic Bias

- Algorithmic bias relates to inherent biases in the design or structure of the AI algorithms themselves.
- It can result from the way features are selected, weighted, or processed during decision-making ([example](#): Ribeiro et. al (2016))



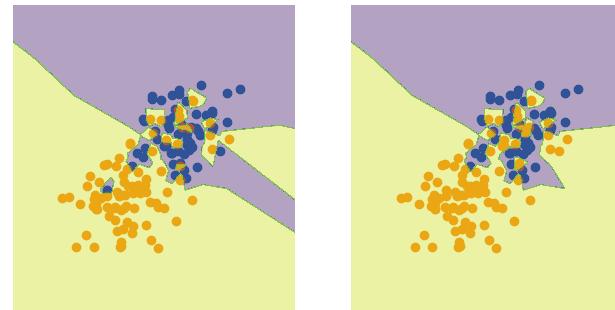
(a) Husky classified as wolf



(b) Explanation

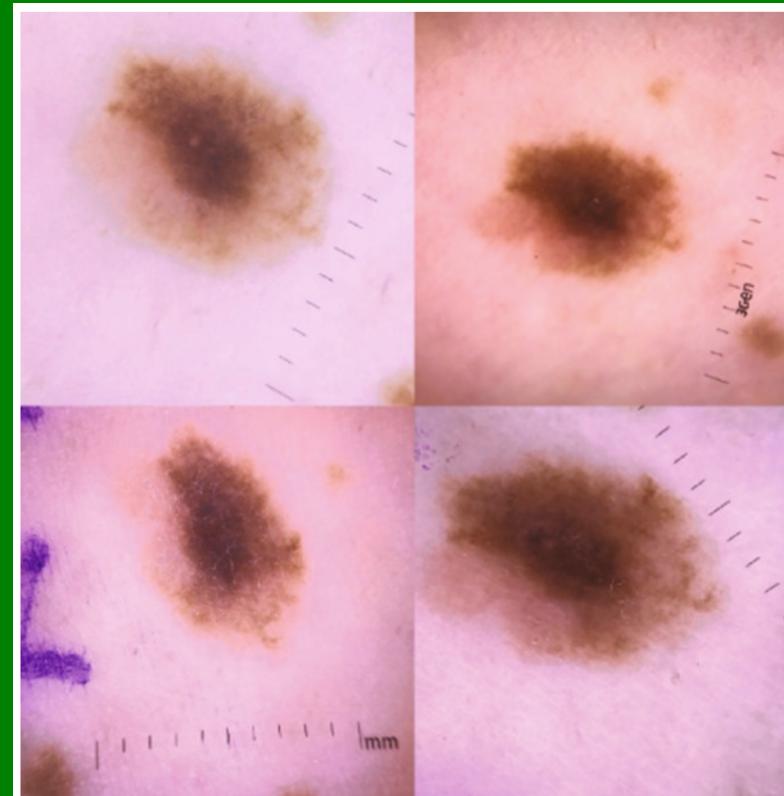
Reinforcement Bias

- Reinforcement bias emerges from the interactions between AI systems and users.
- It results from AI systems learning from user feedback and behavior.
- If users exhibit biased behavior, the AI may reinforce these biases in its responses.
 - See Hidden Risks of Machine Learning Applied to Healthcare ([Adam et. al \(2020\)](#))



Breakout #2

What issues would arise if we trained a melanoma classifier on these sorts of images?



Addressing Bias

Three places where bias can be mitigated

- Pre-processing (what data gets seen)
- In-processing (model training procedure)
- Post-processing (how the model inferences are used)

Diverse and Inclusive Data Collection (pre-processing)

- Collect diverse and representative data to train AI models.
- Ensure that data includes various demographic, geographic, and socio-economic factors.
- Pay special attention to underrepresented or marginalized groups to avoid skewed or biased training data.

Weighting a loss function (in-processing)

- Assume a label y , features x , a protected group $g \in \{A, B\}$, an algorithm $f_\theta(\cdot)$ with learnable parameters θ and a loss function $\ell(\cdot)$

$$\sum_{i=1}^n w_i \cdot \ell(y_i, f_\theta(x_i)), \quad i \in \{A, B\}$$

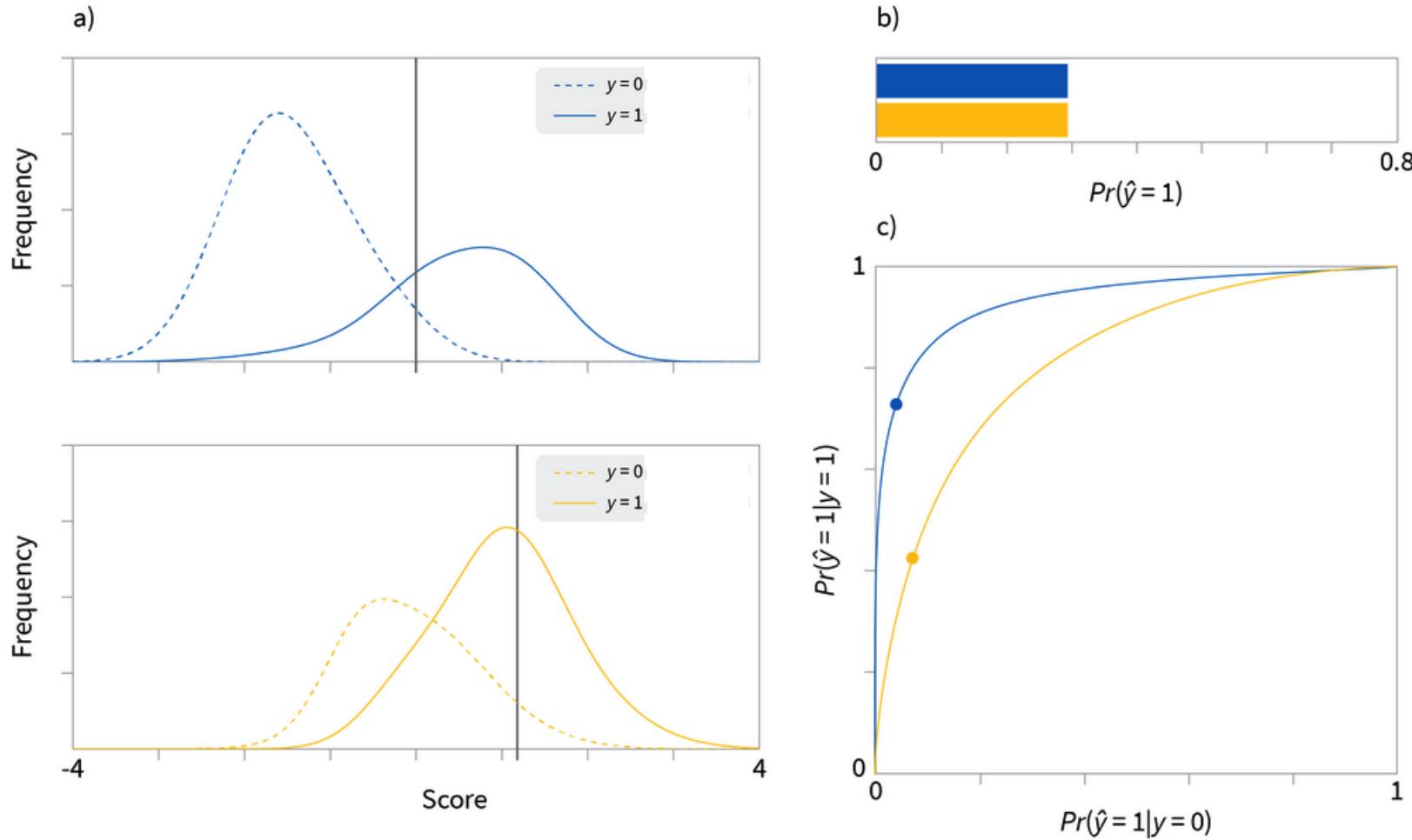
- We can weight a loss function towards whichever group(s) we want to "protect"

Definitions of "fairness" (binary classifier)

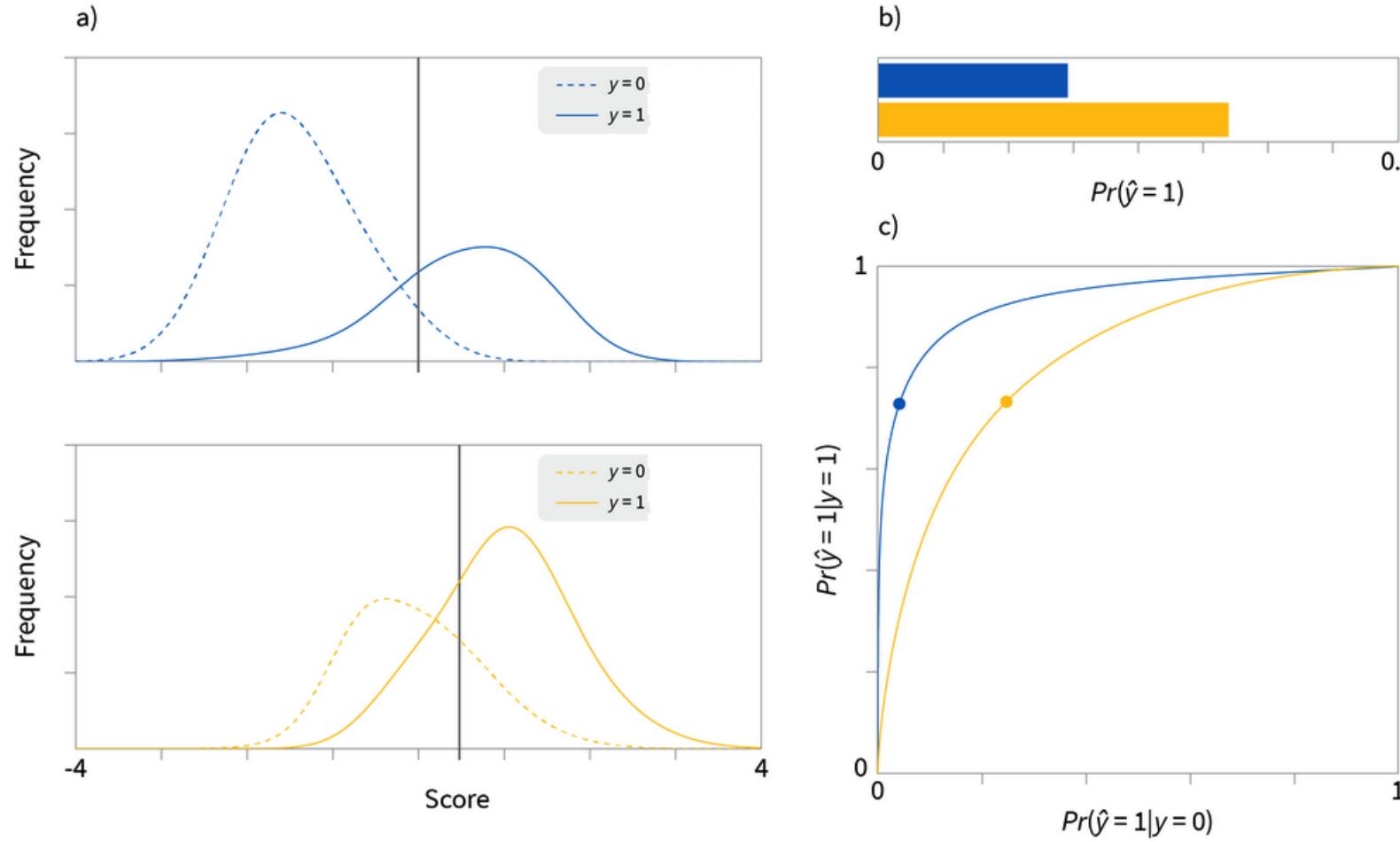
- Recall $\hat{y} = I(f_\theta(x) > t)$
- Demographic parity: $P(\hat{y}|g) \approx P(\hat{y}), \forall g$
- Equality of opportunity: $P(\hat{y}|y = 1, g) \approx P(\hat{y}|y = 1), \forall g$
- Individualized fairness: $P(\hat{y}_i = y|x_i, g_i = A) \approx P(\hat{y}_i = y|x_j, g_j = B), \forall i, j : \text{dist}(x_i, x_j) \approx \text{small}$
- You cannot reconcile these types of fairness: Impossibility theorem
(see [Saravanakumar \(2021\)](#))
- [Examples](#) to follow



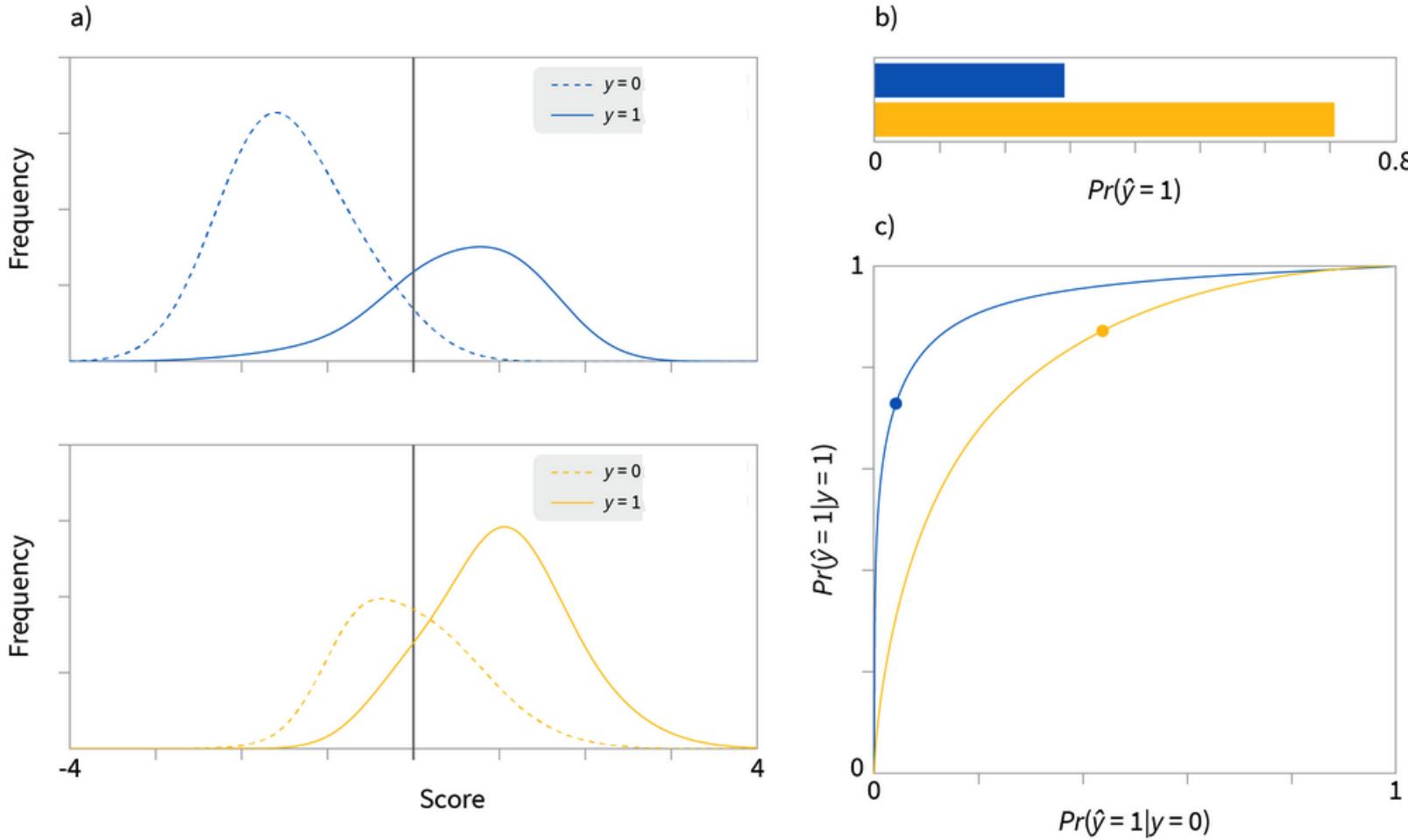
Demographic parity



Equality of opportunity



Individual fairness



Transparency, explainability, monitoring, & feedback

- Make AI models more transparent and interpretable to understand the factors influencing their decisions.
- Implement techniques like explainable AI (XAI) to provide insights into model behavior and allow for the identification and rectification of bias.
- Establish a feedback loop for continuous monitoring and improvement of AI systems' fairness.
- Collect feedback from users and impacted communities to identify and address bias issues as they arise, making ongoing refinements to models and data.

Risk

- Risk in AI refers to the potential negative consequences or uncertainties associated with the development, deployment, and use of artificial intelligence systems.
 - **Data Breaches**
 - Breaches can expose patient information, leading to privacy violations and legal consequences.
 - **Incorrect Diagnoses**
 - AI systems that assist in diagnostics could potentially make incorrect diagnoses, leading to improper treatment and harm to patients.
 - **Legal Liabilities**
 - Healthcare providers using AI systems face legal risks if the technology leads to patient harm, including malpractice claims.

Addressing Risk

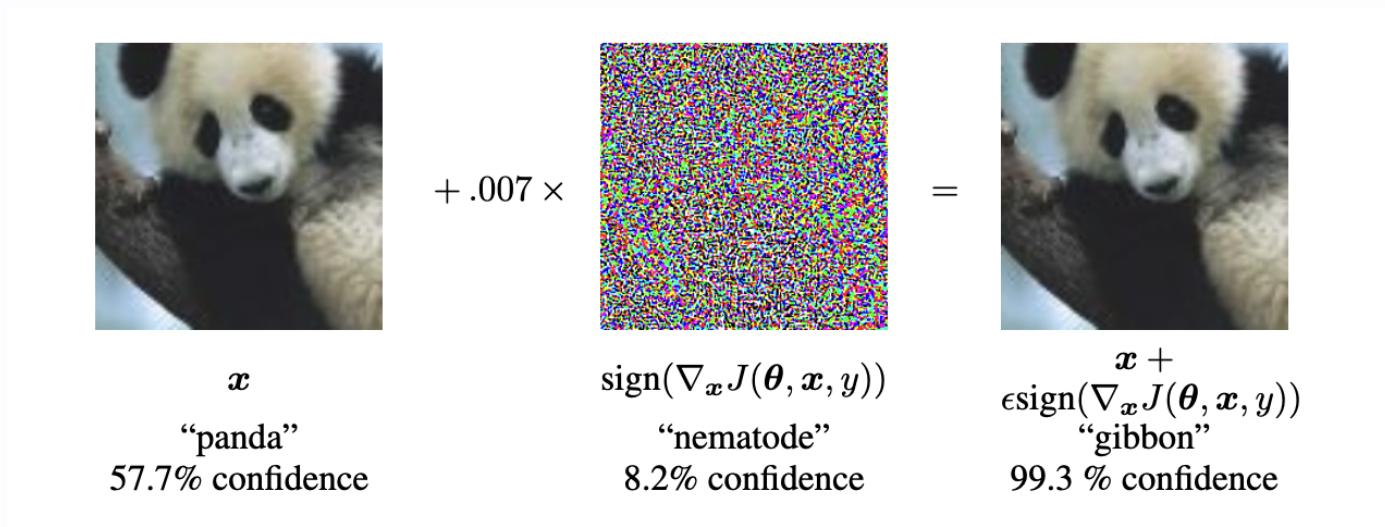
- **Robust Data Security Measures**
 - Ensure compliance with regulations like General Data Protection Regulation (GDPR) and Health Insurance Portability and Accountability Act (HIPAA) to safeguard sensitive health data.
- **Transparent and Explainable AI**
 - Develop AI systems that are understandable and transparent, elucidating how AI decisions are made.
- **Ethical AI Development and Use**
 - Adhere to ethical principles in AI development to ensure fairness, avoid bias, and respect patient autonomy and privacy.
- **Rigorous Testing and Validation**
 - Subject AI systems to extensive testing and validation to confirm their safety and efficacy, and that they perform as intended across diverse patient populations.

Generalization

- Generalization in AI refers to the ability of an AI system or model to perform well on new, unseen data after having been trained on a specific set of data.
- We'll review why ML models often have a hard time generalizing, especially in healthcare

ML models are "extremely sensitive"

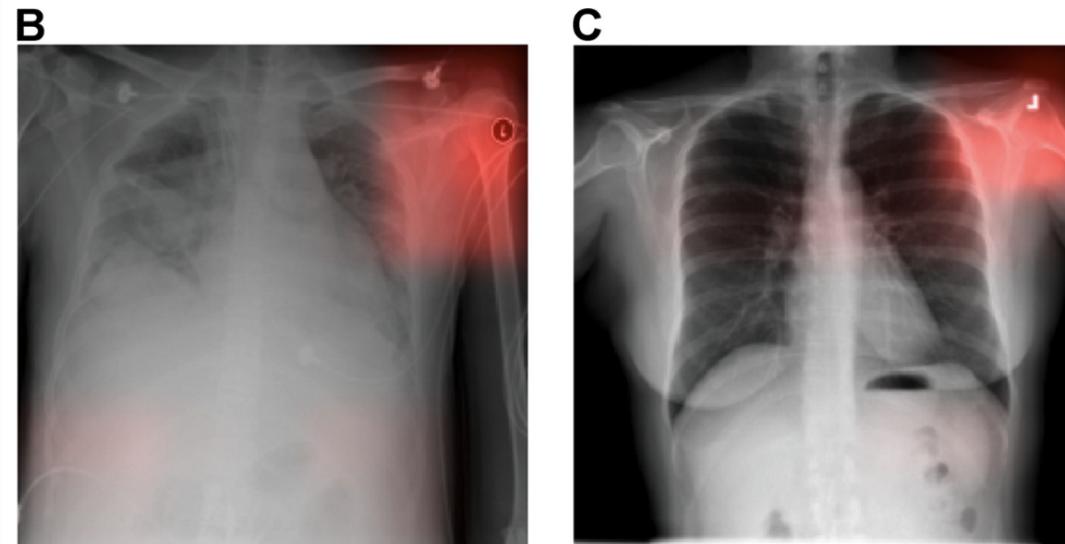
- All deep learning systems can be rendered useless by adversarial attacks



Source: Goodfellow et. al (2015)

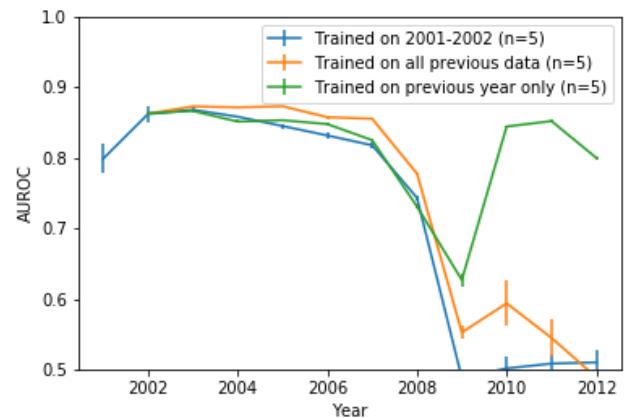
Can be easily tricked (confounded) by artefacts

- Example of CNN picking up on hospital-specific X-ray practices
(source: Zech et. al (2018))



Will often experience model drift

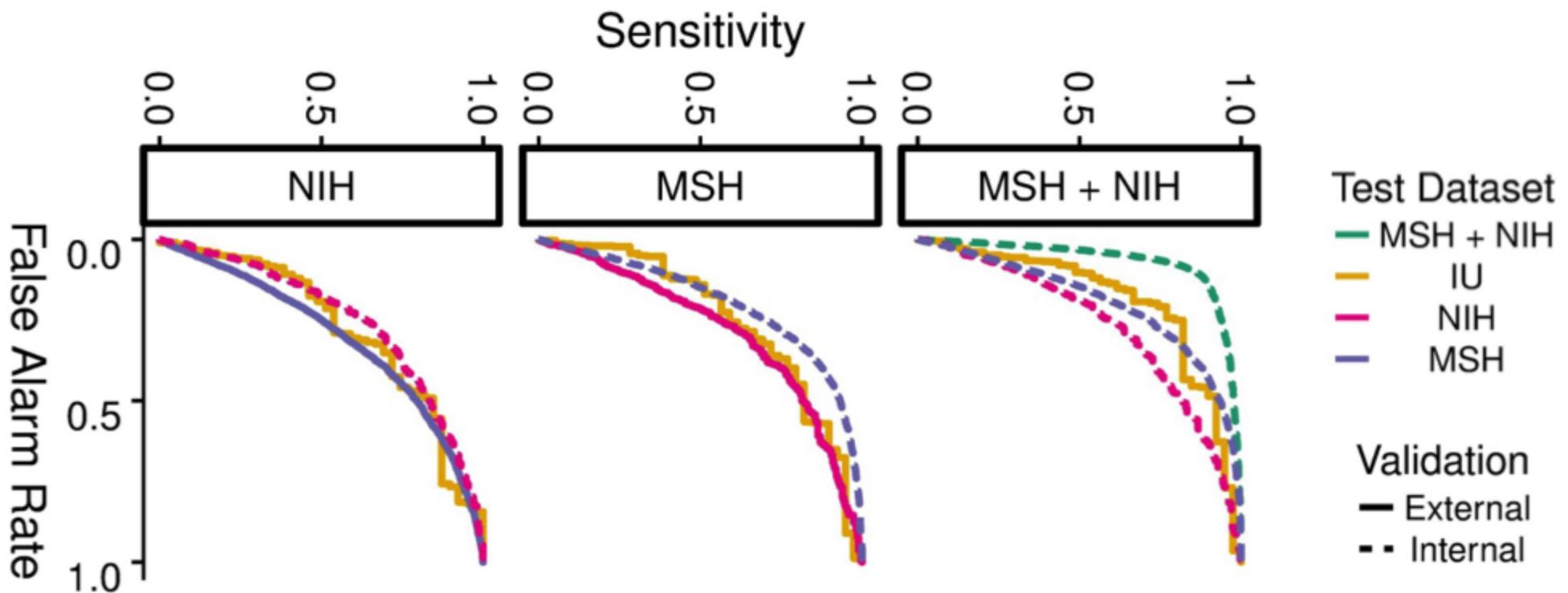
- After a model goes live the performance of the model will often suffer
 - Unconditional label distribution changes
 - Unconditional feature distribution changes
 - Conditional relationship b/w label and features changes



Source: Nestor et. al (2019)

Variation by institution

- We often observe variable performance by institution



Source: Zech et. al (2018)

Best practices around generalization challenges in healthcare

Overfitting vs. Underfitting

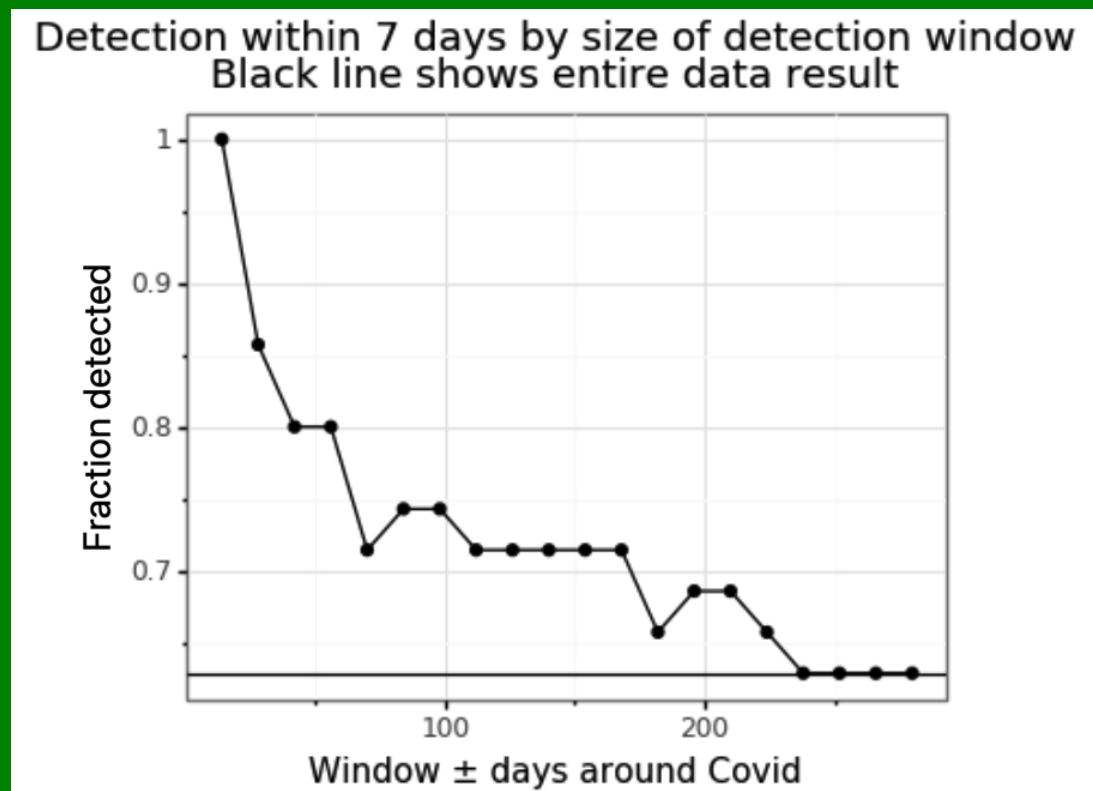
- Good generalization requires balance between overfitting and underfitting.
- Overfitting: Model learns the training data too well & performs poorly on new data.
- Underfitting: Model is too simple to capture the underlying structure of the data & performs poorly on training and new data.

Data diversity and structure

- Healthcare datasets should come from diverse populations with varying demographics, medical histories, and health conditions.
- Ensure multiple institutions are represented
- Data should be split in a way that is representative of future usage

Breakout #3

The following graph shows how the construction of the feature/label space impacts model accuracy. What is driving this result and how would you construct the feature/label space?

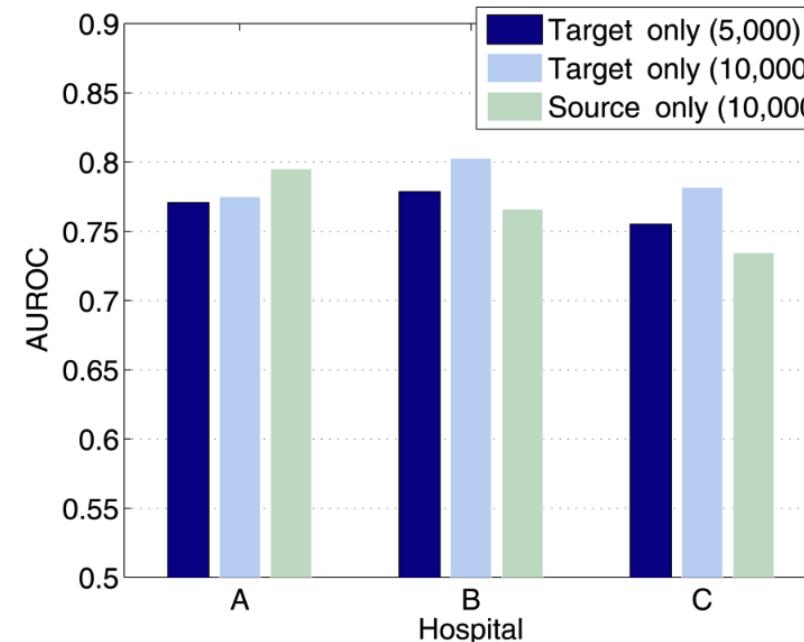


Changing Healthcare Practices and Knowledge

- Healthcare is a rapidly evolving field (i.e., new treatments, diagnostic criteria, and research findings).
- A dedicated data team is often needed to update the data (and possibly training) pipeline for new and emerging data types (recall "conformance")

Transfer learning

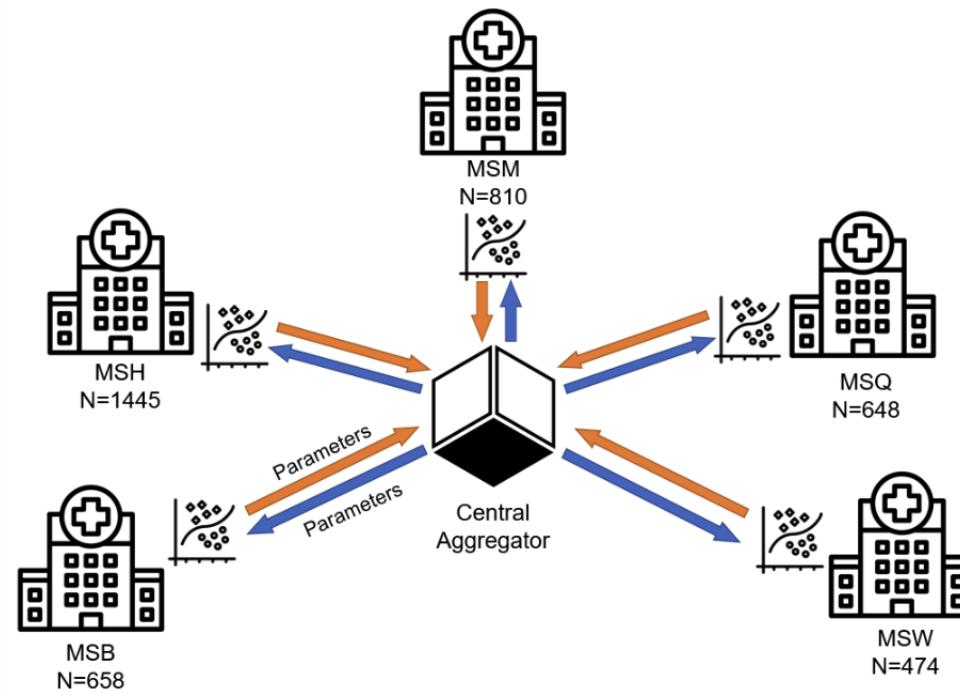
- Transfer learning: involves taking a model that has been trained on one task and adapting it to a different but related task.
 - Can *sometimes* help in situations where there is not enough data for training a model from scratch, leveraging the generalization capabilities learned from the original task.



Source: Wiens et. al (2014)

Federated learning

- Federated learning pools information across for training a machine learning model without data ever needing to be centralized
- Can train more powerful models that generalize without breaching data privacy concerns (speeds up process basically)



Source: Nadkarni et. al (2021)