Perils and Promise of AI/ML in Healthcare

Professor Margrét V. Bjarnadóttir
Promise of AI/ML in Healthcare

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Predicting Colorectal Cancer Mortality: Models to Facilitate Patient-Physician Conversations and Inform Operational Decision Making

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Having accurate, unbiased prognosis information can help patients and providers make better decisions about what course of treatment to take. Using a comprehensive dataset of all colorectal cancer patients in California, we generate predictive models that estimate short-term and medium-term survival probabilities for patients based on their clinical and demographic information. Our study addresses some of the contradictions in the literature about survival rates and significantly improves predictive power over the performance of any model in previously published studies.

Key words: data mining; medical decision-making; survival analysis; personalized medicine

History: Received: March 2016; Accepted: April 2018 by Sergei Savin, after 2 revisions.

1. Introduction

Patients newly diagnosed with a medical condition...
The Knowledge Seeker

Caucasian patients are significantly different from black patients
(Dayal et. al, 1987)

http://spotonlists.com
Caucasian patients are significantly different from black patients
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Race not significant unless considered with SES
(Ward et. al, 2008)
The Knowledge Seeker

Caucasian patients are significantly different from black patients
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Young patients' survival is significantly lower than old patients
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Young patients' survival is significantly lower than old patients (Vironen et al., 1987)

Marriage is significant (Goodwin et al., 1987)

Race not significant unless considered with SES (Ward et al., 2008)

No significant difference between young and old patients (O’Connell et al., 2004)
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Young patients' survival is significantly lower than old patients (Vironen et. al, 1987)

Marriage is significant (Goodwin et. al, 1987)

Race not significant unless considered with SES (Ward et. al, 2008)

No significant difference between young and old patients (O'Connell et. al, 2004)

Marriage not significant if diagnosis and treatment considered (Greenberg et. al, 1987)

No significant difference between young and old patients (O'Connell et. al, 2004)
The Knowledge Seeker
Seeking comprehensive understanding of cancer outcomes

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1. Introduction

Patients newly diagnosed with a medical condition...
Main findings

Some variables are important across time horizons.

Others are only important over short time horizons.

Others still may only appear important for long term survival.
Main findings

The models can with almost certainty, for some patients, predict who will survive and who will not.

Stage IV, hospitalized at the hospital which reported the tumor, received surgery which involved removing lymph node as their first course of treatment.

Stage I, underwent surgery, disposition to home.

Stage is I-III, received surgery as the first course of treatment, disposition is to home or nursing home.
Addressing algorithmic bias and the perpetuation of health inequities: An AI bias aware framework

R. Agarwal, M. Bjarnadottir, L. Rhue, M. Dugas, K. Crowley, J. Clark, G. Gao

A R T I C L E  I N F O

Keywords:
Artificial intelligence
Algorithmic bias
Health disparities
Health equity
Machine Learning Bias
Algorithmic Fairness

A B S T R A C T

The emergence and increasing use of artificial intelligence and machine learning (AI/ML) in healthcare practice and delivery is being greeted with both optimism and caution. We focus on the nexus of AI/ML and racial disparities in healthcare: an issue that must be addressed if the promise of AI to improve patient care and health outcomes is to be realized in an equitable manner for all populations. We unpack the challenges of algorithmic bias that may perpetuate health disparities. Synthesizing research from multiple disciplines, we describe a four-step analytical process used to build and deploy AI/ML algorithms and solutions, highlighting both the sources of bias as well as methods for bias mitigation. Finally, we offer recommendations for moving the pursuit of fairness further.

I N T R O D U C T I O N

With data revealing that a disturbingly disproportionate burden of the adverse outcomes of the COVID-19 pandemic is being borne by communities of color, racial disparities, long present in the US healthcare system, have recently come into sharper focus [1]. Today, health equity is appropriately front and center in public policy discourse: the National Academy of Medicine’s Vital Directions for Health and...
Millions of black people affected by racial bias in health-care algorithms

Study reveals rampant racism in decision-making software used by US hospitals — and highlights ways to correct it.
An objective process on its surface

Bias can enter at any stage from problem definition to bias amplification through...
BRIEF HISTORY OF FAIRNESS IN ML

PAPERS


LOL FAIRNESS!!

OH, CRAP.

Image from: https://towardsdatascience.com/a-tutorial-on-fairness-in-machine-learning-3ff8ba1040cb
A framework to study health inequities; a case study of breast cancer survival
Margret V. Bjarnadottir, Ritu Agarwal, Shana Ntiri, Wedad Elmaghraby, Nawar Shara

Introduction and background

Health inequities across demographic and socio-economic groups are well documented and widely reflected in a variety of healthcare services and outcomes, including screening rates, disease severity at diagnosis, disease incidence, disease prevalence, mortality, survivorship (the morbidity from treatment) and financial burden. It is therefore not surprising that there is a growing need and desire to first understand and subsequently address the presence of such disparities (Best et al, 2022). The phenomenon of health inequity is complex and multi-faceted, and can arise as a result of a confluence of impacting factors (cite: our paper). However, there are limited standardized methodological approaches to understand the contribution and interdependencies of the many factors (e.g. access to care, health literacy) that drive health disparities. Thus, there is a pressing need for techniques that can be used to understand the root causes of disparities.
Using AI to frame the health inequities conversation

The causes of health inequity are complex and intertwined.

![Graph showing the unadjusted and adjusted inequity gaps by stage of cancer, tumor characteristics, and household income.](image)

- The unadjusted inequity gap
- The inequity "explained" by stage of the cancer
- The remaining adjusted inequity gap
Promise of AI in Healthcare
Thank you
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