

A Causal Approach to Predicting Medical Conditions in Machine Learning

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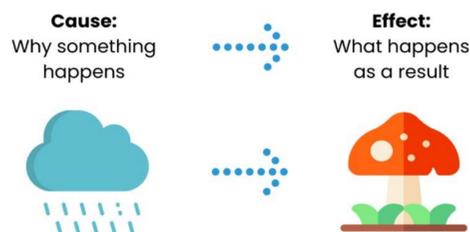
Motivation and Background

Motivation

This research project seeks to apply a causal framework to better introspect and understand machine learning models in the context of health care data. The goal is to better predict medical diagnoses from patient diagnostic data by better understanding the conditions which medical machine learning models will succeed or fail.

Causal Framework

The Kleinberg and Mishra's causal framework, as seen in [1], is adopted and to the context of medical patient diagnosis data. Kleinberg states in [2] that a cause must 1. precede its effect in time and 2. potentially alter the probability of their effects. The idea of a cause altering the probability of the effect could be applied to patient diagnosis data to measure for causal significance.



Motivation and Background

Dataset

The data used in this study is medical patient diagnosis data. The data include 9 target classes:

Target Classes		
In-hospital Mortality	Mortality 6 mo.	Mortality 1 yr.
Mortality 2 yr.	Mortality 5 yr.	Time from PCI to Stroke 6 mo.
Time from PCI to Stroke 1 yr.	Time from PCI to Stroke 2 yr.	Time from PCI to Stroke 5 yr.

PCI stands for Percutaneous Coronary Intervention.

The data also contains 156 features such as gender, age, hypertension, and diabetes to name a few.

Applying the Causal Framework

The Kleinberg causal framework is applied to the patient diagnosis dataset to find causal significance.

1. The prior probability of an effect is calculated.
2. Given a cause, if the probability of that cause \wedge effect is greater than the prior probability, that cause is a prima facie cause.
3. Given that i and j are prima facie causes, if $p_{i,j} - p_{-i,j} > 0$ then i is more likely a cause than j .

$$\epsilon_{K\&M}(i) = \frac{\sum_{j \in R(i)} (p_{i,j} - p_{-i,j})}{|R(i)|}$$

Image from [5]

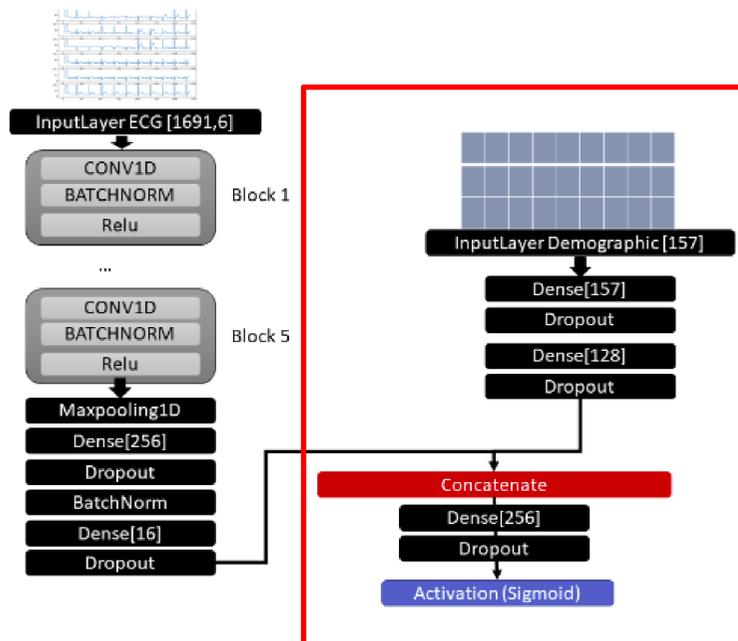
Model Introspection and Predicting Failures

As seen in [4], different machine learning models will be observed to analyze how each model perform in certain aspects. The goal is to discover which models would be better at predicting medical diagnosis given a certain type of data. In addition, we could also predict when models will fail as presented in [3]. By taking the confidence outputs and other factors from the model, we can better understand how a model will perform.

Current Progress

Machine Learning Models

In this work, we study the multi-modal fusion model for prediction of adverse cardiovascular first presented in [6].



The red half of the multi-modal fusion model was used to predict the medical diagnoses from the mayo clinic data. Using these predictions, the model could be further analyzed.

Acknowledgements and References

References

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- [2] Kleinberg, S. (2012). Causality, Probability, and Time. Cambridge: Cambridge University Press. doi:10.1017/CBO9781139207799
- [3] Zhang, P., Wang, J., Farhadi, A., Hebert, M., & Parikh, D. (2014). Predicting Failures of Vision Systems. CVPR.
- [4] Serrano, C. R., & Warren, M. A. (2019). Introspection Learning (Version 1). arXiv. https://doi.org/10.48550/ARXIV.1902.10754
- [5] Shaabani, Guo, R., & Shakarian, P. (2019). Detecting Pathogenic Social Media Accounts without Content or Network Structure.
- [6] Bhattacharya, A., Banerjee, I., & Sanyal, A. (2022). Multi-modal Fusion Model for Predicting Adverse Cardiovascular Outcomes.

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