<u>Academic Statement of Purpose</u>

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Graduate Program: Computer Science and Engineering, PhD

My primary research interests are in AI, specifically within computer vision. I am applying to the PhD program in Computer Science at the University of Michigan to delve deeper into research and tackle challenges in this area. During my undergraduate career, I pursued degrees in both Computer Science and Business Administration. Through multiple upper-level courses in Computer Science, I have built a solid foundation of knowledge in computer vision, machine learning (ML), robotics, and leveraged my skills during two research experiences. Currently, I am actively involved in multiple research projects in the MLD3 lab led by **Professor Jenna Wiens at the University of Michigan (UM)** where I focus on developing algorithms for learning computer vision models that are robust to spurious correlations or 'short cuts'. I also worked with **Professor Mohamed Mostagir in the Ross School of Business** to understand the effects of linking Medicare payments to healthcare quality. Below, I summarize my current research interests and future directions.

Together with Professors Jenna Wiens and David Fouhey, as well as pulmonologist and critical care physician Dr. Michael Sjoding, I am developing multi-modal ML techniques to diagnose patients based on imaging data (e.g., chest x-rays) in addition to clinical variables (e.g., laboratory results) from the electronic health record (EHR). Current approaches for this task rely on images alone [1, 2] and do not transfer across institutions [3]. **We hypothesize that this lack of transportability is due in part to the model taking 'short cuts' (e.g., classifying based on text in the images rather than visible symptoms).** To understand the effects of integrating clinical variables in addition to imaging data, three models were trained on different modalities: imaging data, clinical variables, and a combination of the two. The model trained on solely imaging data relied on features in the images that are not necessarily clinically relevant, such as text. However, a multi-modal approach where clinical variables were used in combination with imaging data resulted in features that reflected visible symptoms in the patients instead of text. These results highlight an opportunity to leverage useful information contained in the electronic health record to develop more robust models.

Similar to 'short cuts', spurious correlations can be present in imaging datasets (e.g., high correlation between how sick a patient is and the machine their image is taken on). Many current approaches to mitigating these spurious correlations in datasets rely on prior knowledge about what the correlations are [4,5]. Due to the large number of spurious correlations that can be unknowingly present, I am developing techniques that mitigate these correlations without requiring prior knowledge of what they are. Our method first injects a bias into the dataset that is correlated with the main task (e.g., we introduce a high correlation between body-mass-index and main task of diagnosing heart failure). We then train a model using a 2-stage approach: first training on a "differential diagnosis," a diagnosis that uses similar visible symptoms as the main task (e.g., pneumonia) and is not correlated with the injected bias, and then use the features that are learned from the differential diagnosis to predict the main task. **We hypothesize that this approach will force the model to learn features from the differential diagnosis that are**

uncorrelated with the injected bias, ultimately leading to predicting the main task without the effects of this bias.

Datasets can also be biased through human intervention, a pressing problem as artificial intelligence becomes more integrated into human facing technology. If a clinician under tests patients from a certain subpopulation (e.g., gender) for a certain disease (e.g., *C. difficile* infection), this can lead to less “positive” labelled examples for a model to learn from, making that subpopulation look low-risk. Models trained on such biased data with the intent of determining high-risk patients (which are then tested for infection) can ultimately exacerbate this bias. I analyzed patient testing rates across race and gender in a dataset used to predict the onset of *C. difficile* infection at Michigan Medicine and discovered no statistically significant difference between subpopulations. However, **these analyses highlight the importance of understanding the source of the data during problem formulation, especially in critical care settings.**

In addition to my research with Professor Wiens, I worked with Professor Mohamed Mostagir to investigate the effects of the Centers for Medicare and Medicaid Services’ (CMS’) efforts in linking Medicare payments to healthcare quality in the inpatient hospital setting. Beginning in 2015, the Hospital Acquired Conditions (HAC) Reduction Program was established, which adjusts payments to hospitals that rank in the worst-performing 25 percent of hospitals with respect to HAC quality measures. I collected data consisting of HAC quality measures for all hospitals affected by the HAC Reduction Program over several years. I then determined the worst-performing hospitals and measured the effects of penalized Medicare payments on their performance in subsequent years.

I developed a passion for teaching through three years as a teaching assistant for a masters level business analytics course. I found great satisfaction in changing students’ perspectives on topics they once thought they were incapable of grasping. After completing my PhD, I strive to continue to be a part of the classroom and create a setting that allows students to thrive in their learning experiences.

I am excited about UM’s program as it develops computer vision techniques that allow agents to understand the world**. My main computer vision interests are two-fold: its interdisciplinary applications and the use of vision to enable agents to interact with the world.** I am particularly interested in the work conducted by **Professors Jenna Wiens and David Fouhey**. Through my work with Professor Wiens, I gained insight into augmenting clinical care with computer vision. Our work focuses on chest x-rays, but there are many medical image modalities (e.g., MRI, CT) that I would be excited to work with. Additionally, I was exposed to Professor Fouhey’s research on 3D understanding through his computer vision course, and am intrigued by the techniques developed in his research that allow intelligent agents to understand the world’s properties. I would be excited to contribute to his work that allows agents to understand the 3D properties of the world, and then use these properties through interactions with the world. The endless range of applications of computer vision are evident. Pursuing a PhD in Computer Science at the University of Michigan will allow me to push forward in this exciting space.

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