Prospectus

Machine Learning Algorithm to Calculate Cobb Angle
(Technical Topic)

Analysis on the Effects of Machine Learning within the Healthcare System
(STS Topic)

By

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On my honor as a University student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments.

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Introduction

Adolescent Idiopathic Scoliosis (AIS) affects up to 3% of children in the United States (U.S.), and it is the most common form of spinal deformation (U.S. National Library of Medicine, 2019). This disease develops in late childhood and results in abnormal curvature of the spine. The cause of this disease is unknown, so Minimally Invasive Spinal Technologies (MIST) LLC is looking to correct the spine once the disease presents itself (U.S. National Library of Medicine, 2019). Currently, scoliosis is diagnosed when the spine has at least a 10^{o} Cobb angle (Bunnell, 2005). The Cobb angle is measured by hand from an X-ray of the patient's spine, as shown in Figure 1 (Safari, Parsaei, Zamani, & Pourabbas, 2019). The current process is prone to error as the doctor will use a ruler, pencil, and protractor to make the measurements. This process also takes time that the doctor could be using to tend to other patients (Safari et al., 2019).

Currently in the healthcare system both patient volume and patient cost are increasing. Bhardwaj and his colleagues argue that machine learning can reduce the costs of the healthcare system while providing patients with better care (Bhardwaj, Nambiar, & Dutta, 2017). As machine learning begins to assist doctors with various pre-diagnostic analyses the cost per patient visit is expected to decrease. This will also allow doctors to spend less time on each patient, allowing more patients to be treated. Additionally, machine learning can reduce the need for patients to go to hospitals, decreasing patient cost and volume. Almost 90% of Emergency Room visits are preventable. Machine learning can diagnose and direct patients to proper care without the patients needing to go to expensive hospitals (Bhardwaj et al., 2017). Our team will develop a completely automated machine learning algorithm to accurately and efficiently calculate Cobb angles from X-ray images. As machine learning is incorporated into the healthcare system in cases similar to our algorithm, it will alter the relationships between stakeholders throughout the sociotechnical system.

Technical Topic

To diagnose scoliosis the curvature of the spine is quantified using a Cobb angle. To calculate the cobb angle doctors will first identify the end vertebrae on an X-Ray and then measure the angle (Gstoettner et al., 2007). The end vertebra is defined as the two vetebrae on either end of the spine that are most tilted (Potter et al., 2005). Then using a pencil and a ruler, physicians will draw lines through the endplates of the end vertebrae. The angle between these two lines will then be measured using a protractor. This is the most commonly used method to find the Cobb angle (Safari et al., 2019).

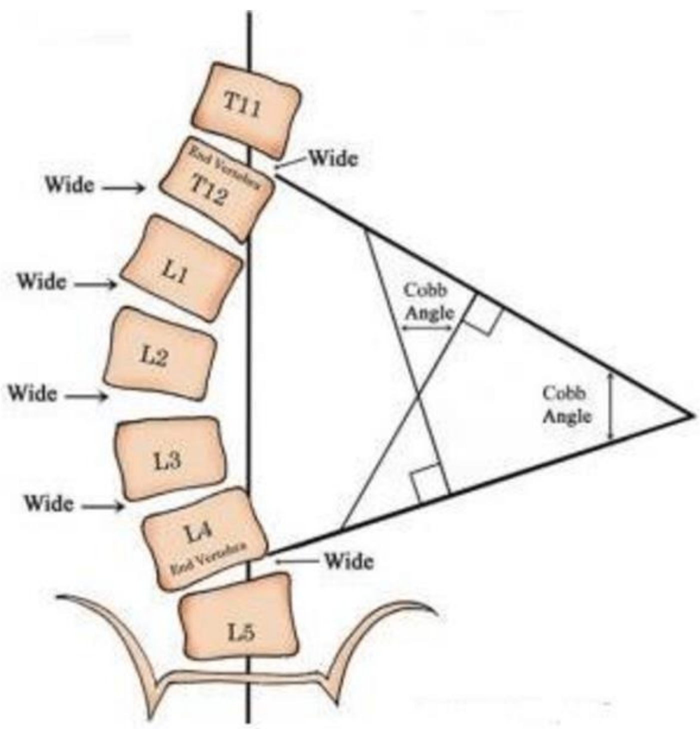

Figure 1. Cobb Angle (Safari et al., 2019)

In recent years this process has begun to be computerized. In 2019 a group from Shiraz, Iran developed the most advanced algorithm for determining Cobb angle of the spine. This algorithm first requires the operator to identify every vertebrae by placing a point somewhere on the vertebrae. These points are then fitted to a 5th order polynomial curve. The algorithm draws two perpendicular lines normal to the inflection points. The Cobb angle between these two lines is then measured. Even with this advanced algorithm the team was only able to achieve 81% accuracy (Safari et al., 2019). We believe that a machine learning algorithm can surpass this result, and eliminate the time and potential errors induced by operator input, i.e. selecting specific points on the vertebrae.

MIST LLC would like us to create a machine learning program that will automatically calculate the Cobb Angle from an X-ray image. The two technologies that will be involved in our capstone will be archived X-rays images and a machine learning algorithm. X-rays are a well-established imaging technique that use a focused beam of electromagnetic to pass through the patient's body, capturing an image of the patient's skeletal structure. They are relatively cheap, and allow physicians to painlessly see inside of a material (National Institute of Biomedical Imaging and Bioengineering, 2017). Bones, such as vertebrae, will absorb large amounts of the X-rays, thus resulting in a higher contrast in the image. Unfortunately. X-rays do expose the patients to radiation. This can be slightly mitigated by placing lead over every part of the patient's body not being imaged. For our capstone we will be utilizing digitalized pictures from X-rays, but we will not be improving on the current X-ray process. These images will be procured and assigned a correct Cobb angle from the UVA hospital archives by the MIST team.

We plan to develop a machine learning program that will analyze each digital X-ray image and correlate the characteristics of the image with a Cobb Angle. Machine learning is a technique that recognizes patterns amongst large sets of data without being explicitly programmed to do a certain task (SAS Insights, 2019). Using machine learning will allow our group to avoid the human error introduced by writing inflexible code. To our knowledge this technique will be the first Cobb angle detection method that will utilize machine learning. Our technique will use a deep learning algorithm to analyze the X-ray images and detect their Cobb angles. We will specifically be using a convolutional neural network as it excels at drawing data accurately from images.[5] My team plans on learning this deep learning through joint classes from the University of Virginia and MATLAB. Additionally, MATLAB provides deep learning toolboxes that we will utilize. We will train this network by allowing it to analyze the X-ray images procured by the MIST team. By giving our program multiple images and their correlated Cobb Angles, the program will become iteratively more accurate (Sharma, 2019).

The machine learning algorithm will improve upon the current art by eliminating human error and saving physicians valuable time. In a reliability analysis of hand-drawn Cobb angles multiple sources of error were identified: "wrong definition of end vertebra, incorrect drawing of the lines through endplates or through the pedicles, drawing of perpendiculars or the measurement of the angle itself" (Gstoettner et al., 2007). Using machine learning will also significantly eliminate the time physicians spend on analyzing the Cobb angle. In one study physicians took 18.96 seconds to calculate the Cobb angle (Wang et al., 2018). Additionally three million new cases of scoliosis are diagnosed in the United States every year (Johns Hopkins Medicine, 2019). For this following calculation I have assumed that the machine learning algorithm would run in the same amount of time it would normally take the physician to grab a pencil, ruler, and a protractor. The machine learning algorithm could save physicians across the United States 15,800 hours per year. This number is artificially low as it does not take into account remeasurement of the Cobb angle during patient checkups, and measurement of patients that have a curved back, but do not have scoliosis. By developing a machine learning technology that will replace human analysis, we hope to benefit both patients and doctors across the healthcare system.

Analysis of Machine Learning in Health Care

This project may contribute to the recent introduction of machine learning into the healthcare system, which is a complex sociotechnical system. The main stakeholders within the healthcare system are hospitals, doctors, patients, and insurance companies. Theoretically, adopting machine learning should be beneficial for all three stakeholders:

- hospitals and doctors would be able to provide better patient care,
- patients would receive a better service for a cheaper price, and
- insurance companies could charge more accurate rates.

As shown in Harrison's paper the theoretical effects of a new artifact do not always align with the actual effects. Unfortunately, Harrison's Interactive Sociotechnical Analysis (ITSA) approach relies heavily on the recursive interactions of the system (Harrison, Koppel, & Bar-Lev, 2007). As machine learning has only been recently introduced in the healthcare system, ITSA cannot best analyze the effect of machine learning. Instead, I will use Latour's Actor Network Theory to analyze how machine learning interacts with stakeholders in the healthcare system. Actor Network Theory (ANT) proposes that people, institutions, and organizations affect the development of a sociotechnical system and that artifacts have an equal role in this process. Latour shows this by analyzing how installing a door groom alters the behavior of people walking through the door (Latour, 1992). As machine learning is such a powerful tool, it will change the behavior of the key stakeholders within the system. For example, it could lower costs to patients resulting in more patients being able to afford healthcare and increasing doctors' patient throughput. It could also possibly be used to alter health insurance policies to maximize their profitability. It is crucial to use ANT as it will allow me to analyze machine learning's interaction with other technologies. Most machine learning in healthcare will build-off of and assist currently existing technologies. For example, radiologists are using machine learning to detect tissues from imaging scans, machine learning algorithms are analyzing medical databases to form disease prediction software, and machine learning algorithms are integrated with ICD10 records to find hospital trends (Bhardwaj et al., 2017; Cabitza, Rasoini, & Gensini, 2017).

In the case of the machine learning algorithm my team is creating, I have provided a ANT model below. The blue boxes denotate technologies, the green ovals denotate actors, and the orange diamonds denotate the relationship. This model is simplified as it assumes all doctors will be employed directly by hospitals. As shown in the diagram the machine learning machine learning algorithm both assists doctors, and analyzes X-rays to diagnose patients. These two actors can then affect the rest of the system besides the government. The patients will pay the insurance company to cover their bills in case of bad health. The insurance company will pay the hospitals for the cost of the patients' visits. The doctors will work at the hospitals, and the hospitals will pay the doctors. The hospitals will also have certain rules for their doctors and enforce a standard of care. The hospital is then regulated by the government to abide by certain practices. By just analyzing our algorithm ANT highlights how machine learning can affect the interactions between the artifacts. This model emphasizes how the introduction of the machine learning algorithm could affect all other actors, besides maybe the government. For example, if the algorithm assists doctors, this could reduce the time they spend treating the patient, which would reduce the cost the insurance company pays the hospitals. This would cause the hospital to pay the doctors less, and the insurance company would charge the patient less. Without ANT, it would be more difficult to see the intricacies of this complex network of relationships.

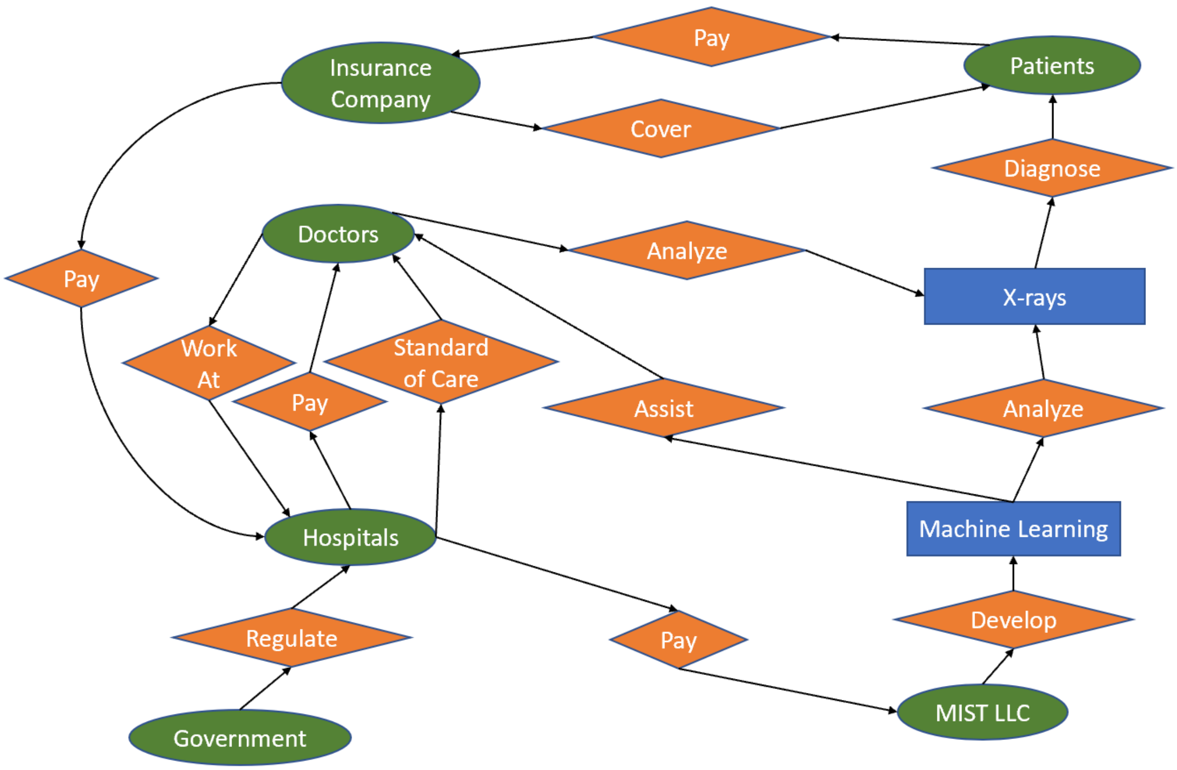

Figure 2. Actor Network Theory Diagram. This diagram shows the ANT web of the machine learning algorithm that my team is producing. (Burke, 2019).

It is important to analyze how machine learning affects the healthcare system as we are not yet sure whether it could produce negative effects. Some researchers speculate that machine learning could actually be harmful for the healthcare system. One detriment of machine learning could the deskilling of the physicians. In one study residents had a 14% decrease in diagnostic accuracy when images were marked with computer-aided detection (Cabitza et al., 2017). Introducing machine learning could also make physicians more data dependent as opposed to looking at the circumstances surrounding the patient. This can be very harmful when the algorithm interprets the data incorrectly. For example, a machine learning program drew a correlation between asthma and a higher chance of surviving pneumonia. This was only due to people with pneumonia and asthma being admitted directly into the ICU. So, the machine learning program misidentified asthma as a protective condition against pneumonia (Cabitza et al., 2017). Using ANT allows me to analyze how relationships within the sociotechnical are changing within the healthcare system.

Research questions and Methods

How and why has the healthcare field begun to adopt machine learning, and how has this affected key stakeholders? To answer this question, I will use case studies and interviews. I will look at companies that utilize machine learning throughout the healthcare industry, and analyze how machine learning is changing the healthcare system. To start, I found a source that lists machine learning companies spread across processes such as smart records, medical imaging and diagnostics, drug delivery and development, medical data, and treatment and prediction of disease (Thomas, 2019). I will compare case studies from published papers to see how the capacities in which machine learning is used will change their effects. While viewing these case studies I will be able analyze the healthcare system before and after machine learning is introduced.

I will also hold interviews across several stakeholders to see how the industry is affected. To start I would like to interview subjects from each of the key stakeholders. For the doctors I will make sure to interview radiologists as machine learning has shown promise in their field

(Bhardwaj et al., 2017). From the government I would want to interview someone in NIH or hospital regulation and ask how they view machine learning. I will also interview management consultants who specialize in the healthcare space. These firsthand accounts will hopefully give me insight across multiple areas of healthcare across multiple years. Since consultants are hired to fix problems, they may be able to identify where machine learning has caused problems within a system, or where it has fixed pre-existing problems. From talking with these stakeholders, I hope to draw insights on the change in relationships machine learning has provoked since it was introduced.

Conclusion

Currently, physicians use a time consuming and inaccurate technique to diagnose scoliosis. This results in inefficient work and poor patient care. The technical project will develop a machine learning algorithm that will accurately and efficiently calculate the Cobb Angle from a digital X-ray image. The goal is to create an algorithm that will increase diagnosis accuracy and therefore improve patient care as compared to the hand drawn method and other algorithms. This new algorithm could save United States' physicians at least 15,800 billable hours every year (Gstoettner et al., 2007; Johns Hopkins Medicine, n.d.). This may result in a two-pronged effect. First, the reduction of time will reduce the cost of the procedure, making scoliosis treatment affordable to more people. Second, since the doctors will spend less time per patient, they will have capacity to treat more patients. I will then analyze how machine learning has been affecting and changing the healthcare system. By analyzing other cases of machine learning in healthcare techniques, I can explore how the introduction of our algorithm will affect the healthcare system.

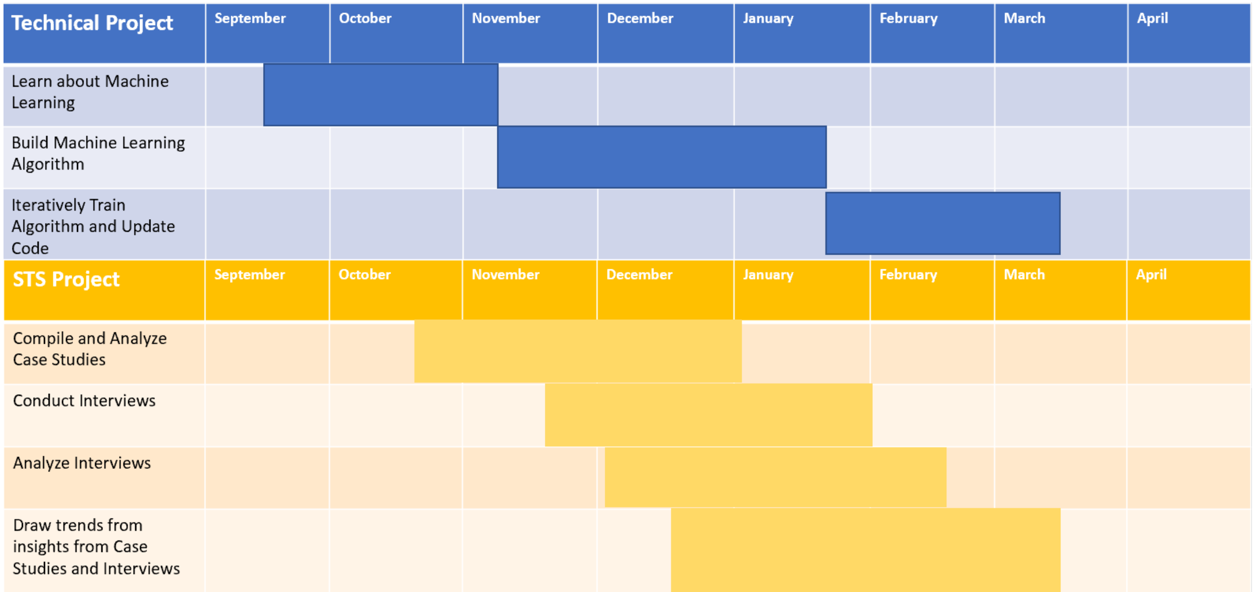

Figure 2. Gantt Chart. That shows my timeline to complete my Technical and my STS project over the next two semesters.

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