ADOPTING MACHINE LEARNING IN MEDICINE: BARRIERS TO ENTRY

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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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Machine learning, a growing field of study, has the potential for greatly advancing medicine. For example, the technical project here uses machine learning for mapping the human brain. In particular, the project aims to discover the differences between the brain maps of people with and without autism. This can drive forward research into diagnosing and understanding autism. Despite the potentially life-saving power of this and other machine learning algorithms, machine learning has seen very little integration into the medical community. The work here aims to discover what is inhibiting the diffusion of machine learning into medicine.

POTENTIAL FOR MACHINE LEARNING IN MEDICINE

Machine learning is defined as the subfield of computer science that "gives computers the ability to learn without being explicitly programmed" (Arthur Samuel, 1959, as cited in Simon, 2013, p. 89). Essentially, machine learning uses large amounts of data to find patterns that yield insights.

Machine learning has great potential benefits in medicine. There are several reasons for this, one of which is the ability to provide more accessible healthcare. First, once implemented, an algorithm has a negligible operating cost, as one must only maintain a computer system instead of staffing medical practitioners. Additionally, machine learning algorithms can reach a broader audience than traditional medical methods. Whereas world-class hospitals are potentially quite distant from patients, an algorithm on the Internet is available worldwide. If a machine learning algorithm is online, anyone with access to the Internet is quickly able to use it, sparing them a possibly expensive trip to the doctor's office or to a faraway hospital. In rural or impoverished areas without access to certain specialized medical tools, online machine learning methods could bring highly specialized healthcare to places it would never have reached otherwise. This is particularly true in areas where healthcare was previously unaffordable.

Machine learning can also provide better care. Machine learning algorithms are not prone to misjudgment, fatigue or other human errors that doctors are prone to, and thus can avoid making fatal mistakes. Moreover, machine learning can lead to medical research that finds new cures and treatments for diseases. For example, the precision-medicine initiative aims to account for variability between individuals, even if they suffer from the same disorders. Collin & Varmux explain that machine learning can help to discover this variability by harnessing the power of large-scale data analysis (2015, p. 1).

Though the current state of machine learning has made reasonable progress, it has seen relatively little adoption by the medical community. This lack of adoption dates back to the early era of machine learning (Kononenko, 2001, p.1) and continues to modern times (Deo, 2015, p. 1928). The main successes of machine learning have happened in academia, rather than in the field. For example, Kononenko writes in 1993 that, even then, machine learning algorithms could accurately prescribe treatments (p. 5), and more recently these algorithms were able to diagnose ailments (Chan et al., 2002, p. 1). Nevertheless, these algorithms are not commonplace in the field today. Perhaps the one place where machine learning has empirically helped medicinal practice is in developing tools that help the interpretation of medical recordings, such as capsule endoscopy, which analyzes the digestive tract (Waljee & Higgins, 2010, p. 1225).

IDENTIFYING ACTORS AND RELATIONSHIPS

Before applying an STS framework, it is crucial to label the actors involved in the diffusion of new medical machine learning technologies. The major actors involved are shown in Figure 1 on page 3, which models relationships between the machine learning community, the medical community, and patients. Note that in all cases relationships are somewhat bidirectional; *i.e.* actors in the diagram always mutually influence each other to some extent. The directionality of arrows shows the larger direction of influence, which corresponds to the direction needed in order to increase the diffusion of machine learning into medicine.

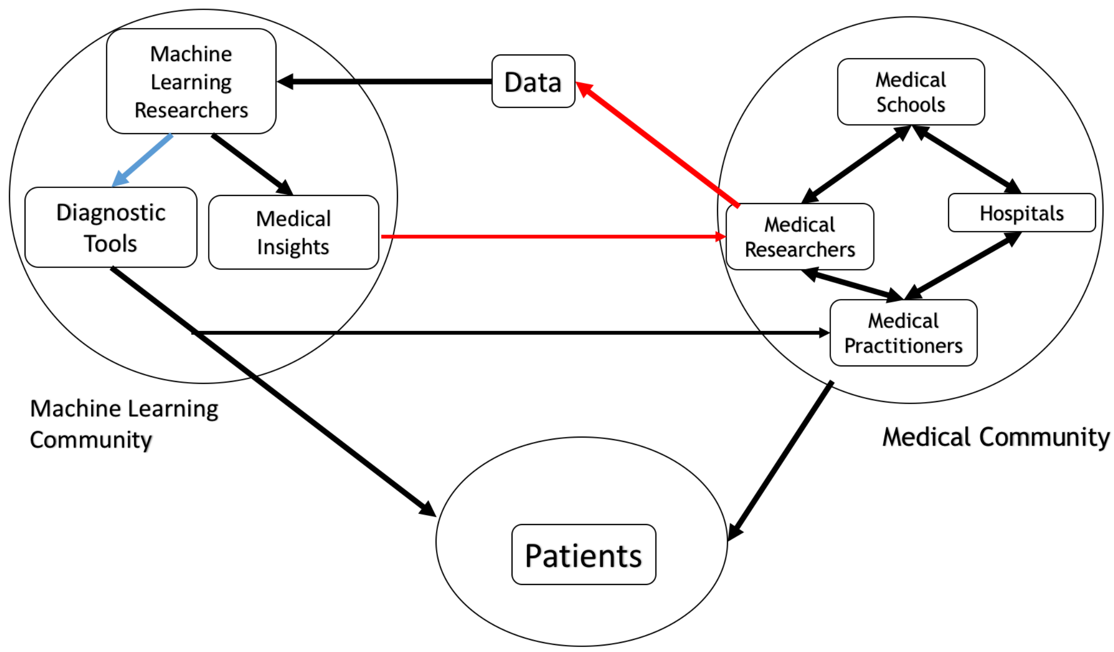

Figure 1: Actors and relationships: A depiction of the actors involved in the diffusion of machine learning into medicine and their relationships. Red lines illustrate organizational barriers, while the blue line highlights technical success (Singh, 2017).

This diagram outlines the basis for an approach to understanding this sociotechnical system. Having defined the actors, we can look towards increasing the amount of interaction with patients, as both the machine learning and medical communities can be expected to increase the welfare of the patients. In Figure 1, there are two connections that do this: the connection from diagnostic tools to patients and the connection from medical practitioners to patients.

In order for the system in Figure 1 to work properly, actors must be must be able to effectively share information and technology via all the connections shown. Thus, in order to find the barriers to diffusion, one must simply examine the connections which are weakest, *i.e.* the connections that have the least communication.

STS FRAMEWORK: PACEY'S TRIANGLE

Having identified the actors, the most important goal can now be addressed: benefitting patients via the untapped potential of machine learning. To analyze this problem, Pacey's triangle is applied (1983, p. 6). Pacey's triangle organizes a technology into three main aspects organizational, technical, and cultural. Note that this problem can also be framed using the diffusion of innovation model originally introduced by Rogers in 1971. However, Pacey's triangle is better suited to this particular problem as it can effectively capture the relationships between the different groups involved in creating the technology. Figure 2 shows Pacey's triangle for machine learning in medicine. Note that the organizational aspects of the technology overwhelm both the technical and cultural aspects. The next three sections go over each of these aspects in detail.

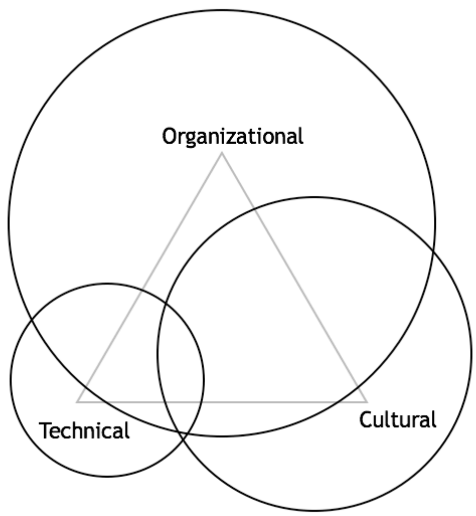

Figure 2: Pacey's triangle for medical machine learning: An illustration of the three aspects from Pacey's triangle applied to machine learning in medicine. Organizational aspects overwhelm the other two. (adapted by Singh from Pacey, 1983, p. 6).

ORGANIZATIONAL IMPEDANCE

The diffusion of machine learning into medicine is overwhelming impeded by two organizational constraints. These two constraints are shown as the red connections in Figure 1 on page 3. The first of these connections is from the medical community to data. In order to succeed, machine learning algorithms require massive amounts of data. However, historically, the medical community has had a poor record of open data-sharing, largely due to the privacy issues that arise in personal medical data (Cleophas, Zwinderman, & Cleophas-Allers, 2013). Coordinating data on this scale requires interaction between different medical departments and institutions. Individually, an institution has little to gain by offering its data to a public server, but releasing private information would be very harmful to an institution's reputation and its patients. Thus, existing biomedical data sets tend to be 10-100-fold too small for effective algorithms (Deo, 2015, p. 1923). In the machine learning community, large-scale datasets often arise as the result of a competition sponsored by a company associated with the release of a large dataset. These competitions are rare in biology, showing an example where bringing the culture of machine learning to biology can go a long way in increasing the capacity of algorithms to successfully develop and for data to be openly shared.

Second, there is a strong barrier existing in the connection from medical insights gained in the machine learning community to medical researchers. This connection effectively represents how machine learning can drive medical research forward. Part of this is because of the opaque nature of machine learning insights. Though they can find patterns that solve problems, it is often difficult to interpret or understand the uncovered patterns. This raises ethical concerns. For example, it is unclear whether the Federal Drug Administration in the United States would allow trials for a drug that is understood via a black box (Deo, 2015, p. 1929). Without a full understanding of a disorder's underlying mechanisms, proceeding medically can have some unintended, and potentially fatal, consequences. This problem is exacerbated by the lack of medical practitioners trained in machine learning who can interpret the complex output that machine learning research yields.

TECHNICAL EXCELLENCE

The technical aspects of machine learning medicine are quite robust. In fact, one connection stands out as being considerably stronger than the rest; it is shown as a blue arrow in Figure 1 on page 3. This connection leads from machine learning researchers to diagnostic tools.

Recently, several websites, including the very popular Web MD (WebMD, 2016), have attempted to offer medical diagnosis using statistical methods over the Internet. These websites, however, generally field the past diagnoses of several doctors rather than running a full-fledged machine learning model, and therefore their diagnoses tend to be unreliable. Nevertheless, despite the limited power of these websites to give accurate diagnoses, they are widely used. With the advent of better algorithms, they can spread quickly to rural and impoverished areas. Part of the reason for the success of these and other online tools is that they are easily monetized, by running ads or charging a fee to use the service. As a result, as machine learning progresses, this field receives large amounts of funding from biotechnology companies and will expand rapidly as technology progresses.

Additionally, there has a been a surge in the number of diagnostic tools made for medical practitioners. This group contains tools, similar to Web MD, but now doctor-facing rather than patient-facing. These tools generally take input from a doctor regarding a patient's symptoms and biostatistics, and then make medical suggestions to the doctor. This is invaluable, as a human doctor's capacity for memory and recall are highly limited, and diagnoses can be greatly aided by even simple algorithms. Over the years, several tools have been developed to solve this problem. Perhaps the first major example is the expert system Mycin (Shortliffe, 2012). Mycin aimed to directly diagnose patients by asking them a sequence of questions in conjunction with a doctor. However, Mycin lacked in popularity largely because it tended to ask what patients felt were too many questions. A more recent example is the commercial product Isabel (Vardell & Moore, 2011). Isabel, instead of directly diagnosing a patient, gives doctors relevant background information and possible diagnoses for the symptoms of a patient. This information can help prevent errors that human doctors make, but Isabel has still seen relatively little adoption.

CULTURAL CONCERNS

All of these tools raise ethical issues when they are considered in a cultural context. First, in order to replace a physician, these systems must be able to promise as high accuracy as that of a human expert. Otherwise, people's lives and healthcare are at stake. Machine learning is much cheaper to maintain than traditional medical practitioners. Thus, hospitals and clinics may be tempted to adopt machine learning in areas where it is not as effective as human experts. To do so would be highly unethical, as it violates the duty of the hospital to care for its patients. Thus, machine learning adoption must be slow and deliberate, with checks built in to ensure that patient care does not drop.

Next, the influx of machine learning into medicine can displace a great number of jobs. This can be particularly harmful as the medical jobs at stake require several years of secondary education and training. However, these jobs are not likely to disappear any time soon. At least with the technology of today and the near future, machine learning is best able to produce tools such as Isabel. These tools aid but cannot replace the experience of a medical practitioner. In any case, the loss of human jobs should be weighed against the lives saved by the technology. Saving human life is inherently moral, and at some point the lives saved by machine learning in medicine would warrant replacing human doctors.

Another consideration arises when these algorithms are put online. As online diagnosis websites provide increasingly accurate results, they can spread healthcare accessibility at a dramatic rate. This is particularly useful for rural and impoverished areas. However, this increases the burden on these freely accessible websites to not spread false diagnoses. People who believe these websites, even when they are wrong, could have their health seriously affected. Perhaps they might even forego a needed trip to the doctor because of a misdiagnosis provided by the website. These situations warrant the use of caution by the websites. They should report, along with their diagnoses, probabilities of error, other potential diagnoses, and recommend consulting a human doctor in necessary situations. As always, these websites must aim to improve the health of the patients who use them, and not be misguided by financial or otherwise immoral incentives.

CASE STUDY: CONNECTOMICS

This section examines Connectomics, the field concerned with mapping the brain, as it directly relates to the technical project here and illustrates some of the issues noted above. Connectomics has gained popularity in recent years for its potential to better understand the brain and diseases effecting the brain (Seung, 2012, p. xxi). Modern brain-imaging techniques such as functional magnetic resonance imaging have produced a great deal of useful data on the human brain in its resting state, which is usually anonymized. Connectomes using this data have been used to understand differences between individuals with typically developing brains and individuals with clinical disorders, particularly autism.

The study of the connectome with machine learning is a major success story of machine learning in medicine. Several large-scale datasets have sprung up for the gathering of large amounts of imaging data for human connectomes (Smith et al., 2013) funded by the extremely large Human Connectome Project in the United States (Milham et al, 2012). This required the coordination of dozens of international sites, and agglomerating data for thousands of patients. This large-scale coordination and funding was able to overcome the major organizational barrier that plague medical machine learning: getting data from the medical community to the machine learning community.

As a result of new data, numerous brain links underlying autism have been found, yielding significant progress in understanding autism (Castellanos, Di Martino, Craddock, Mehta, & Milham, 2013). However, most of this research has been done in the machine learning community, (Uddin, Supekar, & Menon, 2013). Much research must still be done in the machine learning community to completely make sense of this data. Additionally, to be effective this research must overcome the second barrier to machine learning: diffusing from the machine learning community to the medical community. Unless the machine learning research can beget new medicines or treatments, it is unable to help patients suffering from diseases.

CONCLUSIONS: MACHINE LEARNING'S BARRIERS TO MEDICINE

The key finding from the analysis here is that the main barrier to machine learning is organization. Specifically, the barrier can be summarized as a lack of understanding and communication between machine learning researchers and medical practitioners. This barrier, illustrated as a blocked connection in Figure 3, is the root cause of the lack of diffusion and explains many other factors that seem to restrict medical machine learning. By addressing these barriers and then successfully creating technology for patients, machine learning can reasonably diffuse at a much greater rate and be incorporated into medicine. The following sections examine this barrier from either direction and then offer possible solutions to overcoming it.

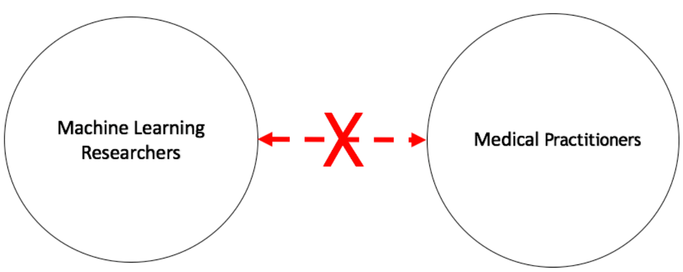

Figure 3: Key insight of this study: The major barrier to medical machine learning is a lack of communication between machine learning researchers and medical practitioners. (Singh, 2017).

From a machine learning researcher's perspective, the major diffusion barrier is the lack of data available from the medical community. As evidenced by the current state of research, it seems that today's machine learning algorithms are immediately applicable, but are lacking the large-scale datasets required to be successful. In other words, inadequacies that seem to be present in machine learning algorithms, the technical portion of Pacey's triangle, can actually be ascribed to a lack of large-scale datasets, the organizational part of Pacey's triangle. Thus, dataset availability for machine learning seems to be the critical bottleneck. Medical datasets are often guarded carefully to protect patient confidentiality, and so it becomes difficult for machine learning researchers to get access to the wide variety of patient records necessary for a strong machine learning algorithm. This is furthered by the fact that medical researchers often do not gather data with machine learning in mind, and often skip details that are only of use to machine learning researchers.

From a medical practitioner's perspective, there seems to be little communication coming from the machine learning community. This bidirectional lack of communication is illustrated by the double arrows on the red line in Figure 3 on page 9. Despite the academic success of many machine learning algorithms, current machine learning methods can be difficult to use, as most researchers do not take the time to make their algorithms available via a website. Unless an algorithm is easy to use, it is unlikely to be adopted. Thus, perhaps the machine learning technologies in medicine will not pick up until they can be easily monetized or until machine learning scientists aim to spread their impact beyond academia.

Social factors in the medical community further strengthen the communication barrier with the machine learning community. First and foremost, doctors do not want to be replaced by these algorithms. This is a very real concern, especially for a profession that involves so much time and financial investment. Additionally, these doctors are rarely familiar with machine learning, as it is not a tenet of medical school. With a lack of trust and training in the technology, it is no surprise that machine learning has seen relatively little adoption by the medical community. The path forward starts with educating medical practitioners about machine learning and its potential benefits in medicine. As medical schools integrate start teaching more about new statistical methods and how to use tools such as Isabel, the new generation of doctors will be more accepting of machine learning. As acceptance grows, increased communication between the two communities will foster more collaboration, research, and ultimately benefit both fields dramatically.

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