Triage, Machine Learning, Algorithms, and Becoming the Borg

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Author’s Note: Bob Wears and I traded e-mail in regard to this editorial before his death in mid-July 2017. Our last “conversation” consisted of notes about algorithms, gaming, and automation. It was a typically Wearsian conversation: geeky, fascinating, and broadly informed. The comments below attempt to bring the notes into a cogent whole. The best thoughts are Bob’s; the clunky writing, mine alone.1 I, along with so many of us at Annals and in emergency medicine, miss him and his special talent for gently pushing us to think more completely and to express ourselves more clearly.

The persistent growth of computerization in the emergency department (ED) is obvious. The typical elements have become so commonplace that they are now part of an assumed background that includes electronic medical record systems, radiology picture archiving and communication systems, computer order entry, ECG storage and retrieval, printed discharge instructions, tracking boards, computerized hospital bed boards, radiofrequency personnel and equipment trackers, barcoded drug delivery, and Health Insurance Portability and Accountability Act–compliant texting.

Departmental transitions from paper to electronic medical record are now relatively rare, with transitions from one electronic medical record to another typical. Enhanced use of information technology in our daily work brings with it an associated transition that has been promised for some time: the movement to clinical decision support and electronic clinical decisionmaking is beginning to take hold. Automated medication interaction and allergy checking are early examples of this transition that point out the often-basic nature of decision support—static rules that bring a question to the clinician when those rules are potentially violated.2 A less readily recognized transition, although equally important, takes the electronic element of our practice from preprogrammed rules to rules that evolve according to the data available. These rules may change without a confirming hand from the clinical team.

In this issue of Annals, Levin et al3 give us a sense of this future. The authors saw a problem and an opportunity in the multitude of patients triaged as Emergency Severity Index level 3, those needing attention and resources but not immediate care. Despite great effort in the application of the index to patient sorting, this category remains a challenge, with a wide swath of illness and acuity.4 The authors asked whether a machine learning approach might better triage this largely undifferentiated group. The potential here is obvious: an automated approach based on a department’s own data might save time and better ensure that patients who need care sooner receive that care more expeditiously. What follows are a few thoughts on what the authors have accomplished, the potential for machine learning in the ED, and the suggestion of caution in handing over higher-level decisionmaking to algorithms, even if they are self-learning.

The novelty in the authors’ work is appealing. The machine approach promises no training books, no quizzes, no attempt to delineate resource use versus acute need for intervention, no variability based on who is conducting the triage, and no gestalt impression of illness. Instead, demographics, vital signs, chief complaint, and medical history feed programming designed to look for patterns that can then be applied against likelihood of needing critical care, emergency procedure, or inpatient hospitalization. No new input is needed beyond assessment of vital signs and the entry of chief complaint; the rest can be obtained from extant records in the medical record.

Although the process appeared to work, the presumption of pure objectivity should give pause. Even seemingly basic tasks as obtaining a chief complaint and vital signs are somewhat subjective efforts. Chief complaint changes frequently from triage to the

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examination room evaluation, and the quantity and content of the additional medical history obtained are framed by the chief complaint.

The point is not that a new triage system performs perfectly, but that it performs better than the old. A more concerning challenge, then, is that it is unclear how to precisely and accurately measure the effectiveness of a triage process. The machine learning algorithm was designed to optimize the need for hospitalization, critical care, or an emergency procedure. This is clarifying in that the goals of triage are cleanly and distinctly defined and we can ask whether these are the most appropriate goals. Several concerns come to mind: these outcomes—critical care, hospitalization, and emergency procedure—may depend on individual practice, local culture, and patient and family desires as much as on physiologic characteristics. The goals of the comparison process, the Emergency Severity Index, are not quite the same in that a major element of the index is the assessment of anticipated resource use. In addition, the index leaves open a path for subjectively assessed degree of pain, distress, or risk and so openly acknowledges the potential benefits of rapid pain control or emergency ED procedural intervention, such as urinary catheterization in the setting of retention or decompression in the setting of pneumothorax. Despite these differences in goals, the authors succeeded in better divvying up the heterogenous pneumothorax. Despite these differences in goals, the authors succeeded in better divvying up the heterogenous Emergency Severity Index level 3. Their success suggests benefit to the machine learning approach, potentially better allowing us to recognize the sick, an activity at the heart of what we do in emergency medicine.

Technical jargon, such as “machine learning” and “predictive analytics,” lacks a firm definition. At the extreme, machine learning and algorithm development suggest the potential for computers to replace us in our roles as diagnosticians and decisionmakers. This extreme, though, is not what the authors imply nor what they have done portends. Rather, they suggest their work is an assistive technology, designed to enhance our own decisions, making us both more efficient and more accurate. For now, their approach suggests that machine learning and algorithms are best treated as an approach by which we, our rapidly amassing data sets, and the computations that pull information from data evolve together to provide better care. Who retains control of which aspects of decisionmaking will be a clinical challenge; whether these remain assistive technologies or whether we should prepare to be assimilated are questions for tomorrow.

Cathy O’Neil, a mathematician, wrote of the dangers of algorithmic approaches and suggested questions we should ask as self-learning tools evolve. She emphasized the need to understand what feeds the algorithm and how it might evolve. She warned that assistive algorithms tend to become self-fulfilling processes. Consider that if the triage score predicts hospitalization at a high rate, perhaps greater than 80%, at what point does the prediction of hospitalization become the reason for hospitalization? How do we know when the algorithm has moved from assistive to determinative? An effective algorithm ultimately makes predictions that are self-fulfilling and therefore hard to change in part because it is hard even to see what is happening.

Machine learning based on extant data sets also incorporates and consolidates the decisionmaking of human processes, here the interpretation of medical history and chief complaint, along with decisions to hospitalize or to place a patient in critical care. Rather than turning toward more objective or biological criteria, the algorithm solidifies the human frailty of previous decisions because it incorporates the individual, institutional, and societal biases already incorporated in the database. On this account, we might ask of this machine learning approach whether it is advancing the goals of triage or whether it is consolidating the flawed processes already inherent in our decisionmaking approach. Most likely, it is doing a bit of both, and separating the 2 becomes a challenge for future work.

The research model of algorithm development and testing, as conducted here, assumes a static environment. From a large database, a portion of the sample is used for algorithm development and the remainder for testing. Questions of whether and how the algorithm might evolve over time are left open. In the case of triage and the prediction of hospitalization, this is particularly important as we work to shift care to the outpatient setting. How active intervention in clinical care meshes with an established algorithm, even one with the potential for self-learning, remains as sticky a question as any implementation of new technology.

In addition, the concepts of self-learning do not necessarily include self-testing. The process is designed, as more data become available, to become more accurate. After an algorithm is implemented, however, it becomes less likely that it will again be tested against alternatives. Instead, it becomes part of “how we do things” and might be as difficult to challenge as any policy or procedure. The machine learning process is unlikely ever to ponder whether triage is even necessary or whether the goals of machine learning, once set, continue to match the clinical goals of emergency medicine. These sorts of questions become important as the clinical goals evolve with the role of emergency medicine within the context of the larger medical system.
For now, what can we take away from the work of Levin et al? We may have a better way to divvy up the diversity of Emergency Severity Index level 3. Machine learning and clinical algorithms have arrived in emergency medicine, bringing with them potential benefit and risk. Knowing the data and the process of the algorithm is at once difficult and essential. We need a firm understanding of what we are trying to accomplish. Testing and reevaluation might be built into the implementation. We must remain vigilant about whether algorithms are helping or impelling—and about whether we are assimilating or being assimilated.

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REFERENCES

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