Annals of Internal Medicine

What Can Medical Education Learn From Facebook and Netflix?

Shiv M. Gaglani, BA, and M. Ryan Haynes, PhD

We had a sobering realization during our first semester in medical school: The Web sites that society's future physicians use to socialize (Facebook) and watch television (Netflix) are managed by more sophisticated algorithms than the tools we use to learn medicine. These data-driven companies have developed interfaces and algorithms to capitalize on the modern "attention economy," and they measure success through such metrics as "daily active users" and "time on site." They analyze millions of data points on individual and group use ("Big Data") to develop personalized recommendations, among other techniques, that keep users engaged (1). Given our backgrounds in neuroscience and computer science, we decided to ask whether similar methods could be applied to medical education and discuss potential opportunities and barriers to these applications.

Medical institutions currently rely on self-reported survey data to understand trainee behaviors and perspectives. A neutral, data-driven approach would be to track learner statistics, such as the frequency and duration of time devoted to viewing course documents and answering practice questions. For example, we created a Web- and mobile-learning platform (www.osmosis.org)—used by nearly 10 000 medical students who have collectively answered questions more than 1.8 million times—that collects performance, duration, recency, confidence, and rating metrics. The site allows us to understand study behavior over time and identify areas of potential improvement (Haynes MR, Gaglani SM, Mitchell TR, DeLeon V, Goldberg H. Learning through Osmosis: a collaborative platform for medical education. In review.).

As another example, lecture remains a very common instructional format at U.S. medical schools (2); as a result, analysis of student-viewing patterns of recorded lectures may generate insights for curricular improvement. Many students, in some cases as many as 80% (3), choose recorded lectures over live ones because they can be paused, rewound, and played at various speeds. This generates data that may be used to create heat maps of individual lectures. Suppose 50 students watch a recorded lecture and 30 of them pause and rewind the video at time point 28:30. It would be statistically possible to infer that the concept being discussed at this point was unclear, and the professor involved could be notified with actionable insights.

The Liaison Committee on Medical Education requires institutions to track time spent in lecture and small groups, as well as which topics are covered throughout the curriculum (4). Despite modern learning management systems, this manual, labor-intensive process takes time away from staff that might otherwise devote more effort to improving curricula. Much of this information can be mined directly from the course documents and refined by crosscomparison with the calendar. For example, a 40-slide PowerPoint file probably represents a lecture, whereas a 3-page Word document with header text that reads "small group" can be readily identified. In this way, curricular mapping can be automated.

By performing full-text extraction and natural language processing on these documents, the curriculum can be interrogated for recurring themes, unnecessary redundancies, and content gaps. A visual timeline that illustrates when certain topics are covered can be constructed (http: //vimeo.com/70907698). For example, when a hematology professor uploads her slides on sickle cell disease, she should receive notification when the students were exposed to the oxyhemoglobin dissociation curve and related material.

Although improvements in the curriculum should lead to increased student engagement and knowledge retention, these goals can be directly accomplished through personalized recommendations. Sites, such as Amazon and Netflix, leverage data to make relevant recommendations to users about what to buy or watch. Similarly, data on student use can be analyzed to generate relevant suggestions based on interests and priorities. For example, if a student spends more time on average viewing documents in the neurology versus the cardiology block, it can be inferred that she is either more interested in or confused by the former's subject material. In both cases, it would be worthwhile to suggest helpful resources, such as explanatory multimedia and practice questions, to the student.

Combined with natural language processing of course documents, this user information can further be leveraged to bridge the gap between the curriculum and real-life context. Students may benefit from suggestions of recent PubMed articles, such as those written by their instructors, or publicly available patient accounts related to their didactic content, which will further serve to improve knowledge retention. For example, we remember bleomycin's key side effect, pulmonary fibrosis, by drawing on the anecdote of Lance Armstrong, who declined the drug in 1996 when he had testicular cancer to preserve his cycling career (5). Integrating various sources, ranging from RSS feeds of academic journals to Twitter accounts of patient advocacy groups, will provide additional real-world relevance to the

The primary barrier to implementing these applications is that data need to be mined directly from an institution's educational software. Many medical schools have fragmented educational technologies that often do not collect or store these user data and may include a legacy or home-grown learning management system, separate content management system, video-hosting service, testing platform, calendar application, and portfolio or patient tracker. Because of this fragmentation, medical students are increasingly turning toward more advanced and userfriendly Web technologies for their educational needs (6). Fortunately, these tools may enable the aforementioned data-driven applications.

Although promising, these approaches are not perfect and thus may be most beneficial when combined with human insight so that learners are provided with relevant and accurate resources. For example, rather than creating content de novo, educators may curate content, such as YouTube videos (7), that can then be automatically recommended. Even self-directed "digital natives" will still require capable guides on the path to learning an increasingly complex and voluminous body of medical information (8). This being said, we are enthused by the opportunities that data-driven approaches present for improving medical education and are hopeful that forward-looking institutions will begin to apply them.

From Johns Hopkins University School of Medicine, Baltimore, Maryland.

Acknowledgment: The authors thank Johns Hopkins School of Medicine professors Catherine DeAngelis, MD, for her help with editorial review, and Harry Goldberg, PhD, and Patricia Thomas, MD, for their insights into curricular design. These contributors received no compensation for their assistance.

Financial Support: In part by the DreamIt Health Technology Accelerator (Philadelphia, Pennsylvania), and the PhD Innovation Initiative Grant from the Johns Hopkins Office of the Provost (Baltimore, Maryland).

Disclosures: Disclosures can be viewed at www.acponline.org/authors /icmje/ConflictOfInterestForms.do?msNum=M13-2286.

Requests for Single Reprints: Shiv M. Gaglani, BA, 733 North Broadway, Suite 137, Baltimore, MD 21205-2196; e-mail, sgaglani@jhmi.edu.

Current author addresses and author contributions are available at www.annals.org.

Ann Intern Med. 2014;160:640-641.

References

- 1. Mayer-Schönberger V, Cukier K. Big Data: A Revolution That Will Transform How We Live, Work, and Think. New York: Houghton Mifflin; 2013.
- 2. Barzansky B, Etzel SI. Medical schools in the United States, 2011-2012. JAMA. 2012;308:2257-63. [PMID: 23212507]
- 3. Kanter SL. To be there or not to be there: is attendance really the question? [Editorial]. Acad Med. 2012;87:679. [PMID: 22643365]
- 4. Liasion Committee on Medical Education. LCME/CACMS guide to the institutional self-study full accreditation, 2014-2015. Washington, DC: Liasion Committee on Medical Education; 2013. Accessed at www.lcme.org/publications .htm on 29 November 2013.
- 5. Johanson P. Lance Armstrong: A Biography. Santa Barbara, CA: Greenwood Biographies; 2011.
- 6. Hollinderbäumer A, Hartz T, Uckert F. Education 2.0—how has social media and Web 2.0 been integrated into medical education? A systematical literature review. GMS Z Med Ausbild. 2013;30:Doc14. [PMID: 23467509]
- 7. Raikos A, Waidyasekara P. How useful is YouTube in learning heart anatomy? Anat Sci Educ. 2014;7:12-8. [PMID: 23564745]
- 8. Kirschner PA, Merriënboer JJ. Do learners really know best? Urban legends in education. Educational Psychologist. 2013;48:169-83.

6 May 2014 Annals of Internal Medicine Volume 160 • Number 9 641

Annals of Internal Medicine

Current Author Addresses: Mr. Gaglani and Dr. Haynes: Johns Hopkins University School of Medicine, 733 North Broadway, Suite 137, Baltimore, MD 21205-2196.

Author Contributions: Conception and design: S.M. Gaglani, M.R. Haynes.

Analysis and interpretation of the data: S.M. Gaglani.

Drafting of the article: S.M. Gaglani, M.R. Haynes.

Critical revision of the article for important intellectual content: S.M. Gaglani, M.R. Haynes.

Final approval of the article: S.M. Gaglani, M.R. Haynes.

Administrative, technical, or logistic support: S.M. Gaglani.

www.annals.org 6 May 2014 Annals of Internal Medicine Volume 160 • Number 9

Copyright © American College of Physicians 2014.