

¹ Text embedding models yield high-resolution insights
² into conceptual knowledge from short multiple-choice
³ quizzes

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⁵ **Abstract**

⁶ We develop a mathematical framework, based on natural language processing models, for track-
⁷ ing and characterizing the acquisition of conceptual knowledge. Our approach embeds each
⁸ concept in a high-dimensional representation space, where nearby coordinates reflect similar or
⁹ related concepts. We test our approach using behavioral data from participants who answered
¹⁰ small sets of multiple-choice quiz questions interleaved between watching two course videos
¹¹ from the Khan Academy platform. We apply our framework to the videos' transcripts and
¹² the text of the quiz questions to quantify the content of each moment of video and each quiz
¹³ question. We use these embeddings, along with participants' quiz responses, to track how the
¹⁴ learners' knowledge changed after watching each video. Our findings show how a small set of
¹⁵ quiz questions may be used to obtain rich and meaningful high-resolution insights into what
¹⁶ each learner knows, and how their knowledge changes over time as they learn.

¹⁷ **Keywords:** education, learning, knowledge, concepts, natural language processing

¹⁸ **Introduction**

¹⁹ Suppose that a teacher had access to a complete, tangible “map” of everything a student knows.
²⁰ Defining what such a map might even look like, let alone how it might be constructed or filled in, is
²¹ itself a non-trivial problem. But if a teacher *were* to gain access to such a map, how might it change
²² their ability to teach that student? Perhaps they might start by checking how well the student
²³ knows the to-be-learned information already, or how much they know about related concepts.
²⁴ For some students, they could potentially optimize their teaching efforts to maximize efficiency
²⁵ by focusing primarily on not-yet-known content. For other students (or other content areas), it
²⁶ might be more effective to optimize for direct connections between already known content and
²⁷ new material. Observing how the student’s knowledge changed over time, in response to their
²⁸ teaching, could also help to guide the teacher towards the most effective strategy for that individual
²⁹ student.

³⁰ A common approach to assessing a student’s knowledge is to present them with a set of quiz
³¹ questions, calculate the proportion they answer correctly, and provide them with feedback in the
³² form of a simple numeric or letter grade. While such a grade can provide *some* indication of whether
³³ the student has mastered the to-be-learned material, any univariate measure of performance on a
³⁴ complex task sacrifices certain relevant information, risks conflating underlying factors, and so on.
³⁵ For example, consider the relative utility of the theoretical map described above that characterizes
³⁶ a student’s knowledge in detail, versus a single annotation saying that the student answered 85%
³⁷ of their quiz questions correctly, or that they received a ‘B’. Here, we show that the same quiz data
³⁸ required to compute proportion-correct scores or letter grades can instead be used to obtain far
³⁹ more detailed insights into what a student knew at the time they took the quiz.

⁴⁰ Designing and building procedures and tools for mapping out knowledge touches on deep
⁴¹ questions about what it means to learn. For example, how do we acquire conceptual knowledge?
⁴² Memorizing course lectures or textbook chapters by rote can lead to the superficial *appearance*
⁴³ of understanding the underlying content, but achieving true conceptual understanding seems to
⁴⁴ require something deeper and richer. Does conceptual understanding entail connecting newly

45 acquired information to the scaffolding of one’s existing knowledge or experience [4, 9, 11, 12, 25,
46 56]? Or weaving a lecture’s atomic elements (e.g., its component words) into a structured network
47 that describes how those individual elements are related [35, 60]? Conceptual understanding
48 could also involve building a mental model that transcends the meanings of those individual
49 atomic elements by reflecting the deeper meaning underlying the gestalt whole [32, 36, 53, 59].

50 The difference between “understanding” and “memorizing,” as framed by researchers in ed-
51 ucation, cognitive psychology, and cognitive neuroscience [e.g., 20, 23, 28, 36, 53], has profound
52 analogs in the fields of natural language processing and natural language understanding. For
53 example, considering the raw contents of a document (e.g., its constituent symbols, letters, and
54 words) might provide some clues as to what the document is about, just as memorizing a pas-
55 sage might provide some ability to answer simple questions about it. However, text embedding
56 models [e.g., 5, 6, 8, 10, 13, 34, 43, 61] also attempt to capture the deeper meaning *underlying* those
57 atomic elements. These models consider not only the co-occurrences of those elements within and
58 across documents, but (in many cases) also patterns in how those elements appear across different
59 scales (e.g., sentences, paragraphs, chapters, etc.), the temporal and grammatical properties of the
60 elements, and other high-level characteristics of how they are used [37?]. To be clear, this is not
61 to say that text embedding models themselves are capable of “understanding” deep conceptual
62 meaning in any traditional sense. But rather, their ability to capture the underlying *structure* of
63 text documents beyond their surface-level contents provides a computational framework through
64 which those document’s deeper conceptual meaning may be quantified, explored, and understood.
65 According to these models, the deep conceptual meaning of a document may be captured by a
66 feature vector in a high-dimensional representation space, wherein nearby vectors reflect concep-
67 tually related documents. A model that succeeds at capturing an analogue of “understanding” is
68 able to assign nearby feature vectors to two conceptually related documents, *even when the specific*
69 *words contained in those documents have limited overlap*. In this way, “concepts” are defined implicitly
70 by the model’s geometry [e.g., how the embedding coordinate of a given word or document relates
71 to the coordinates of other text embeddings; 48].

72 Given these insights, what form might a representation of the sum total of a person’s knowledge

73 take? First, we might require a means of systematically describing or representing (at least some
74 subset of) the nearly infinite set of possible things a person could know. Second, we might want to
75 account for potential associations between different concepts. For example, the concepts of “fish”
76 and “water” might be associated in the sense that fish live in water. Third, knowledge may have
77 a critical dependency structure, such that knowing about a particular concept might require first
78 knowing about a set of other concepts. For example, understanding the concept of a fish swimming
79 in water first requires understanding what fish and water *are*. Fourth, as we learn, our “current
80 state of knowledge” should change accordingly. Learning new concepts should both update our
81 characterizations of “what is known” and also unlock any now-satisfied dependencies of those
82 newly learned concepts so that they are “tagged” as available for future learning.

83 Here we develop a framework for modeling how conceptual knowledge is acquired during
84 learning. The central idea behind our framework is to use text embedding models to define the
85 coordinate systems of two maps: a *knowledge map* that describes the extent to which each concept is
86 currently known, and a *learning map* that describes changes in knowledge over time. Each location
87 on these maps represents a single concept, and the maps’ geometries are defined such that related
88 concepts are located nearby in space. We use this framework to analyze and interpret behavioral
89 data collected from an experiment that had participants answer sets of multiple-choice questions
90 about a series of recorded course lectures.

91 Our primary research goal is to advance our understanding of what it means to acquire deep,
92 real-world conceptual knowledge. Traditional laboratory approaches to studying learning and
93 memory (e.g., list-learning studies) often draw little distinction between memorization and under-
94 standing. Instead, these studies typically focus on whether information is effectively encoded or
95 retrieved, rather than whether the information is *understood*. Approaches to studying conceptual
96 learning, such as category learning experiments, can begin to investigate the distinction between
97 memorization and understanding, often by training participants to distinguish arbitrary or random
98 features in otherwise meaningless categorized stimuli [1, 17, 18, 21, 26, 51]. However the objective
99 of real-world training, or learning from life experiences more generally, is often to develop new
100 knowledge that may be applied in *useful* ways in the future. In this sense, the gap between modern

learning theories and modern pedagogical approaches that inform classroom learning strategies is enormous: most of our theories about *how* people learn are inspired by experimental paradigms and models that have only peripheral relevance to the kinds of learning that students and teachers actually seek [23, 36]. To help bridge this gap, our study uses course materials from real online courses to inform, fit, and test models of real-world conceptual learning. We also provide a demonstration of how our models can be used to construct “maps” of what students know, and how their knowledge changes with training. In addition to helping to visually capture knowledge (and changes in knowledge), we hope that such maps might lead to real-world tools for improving how we educate. Taken together, our work shows that existing course materials and evaluative tools like short multiple-choice quizzes may be leveraged to gain highly detailed insights into what students know and how they learn.

Results

At its core, our main modeling approach is based around a simple assumption that we sought to test empirically: all else being equal, knowledge about a given concept is predictive of knowledge about similar or related concepts. From a geometric perspective, this assumption implies that knowledge is fundamentally “smooth.” In other words, as one moves through a space representing an individual’s knowledge (where similar concepts occupy nearby coordinates), their “level of knowledge” should change relatively gradually. To begin to test this smoothness assumption, we sought to track participants’ knowledge and how it changed over time in response to training. Two overarching goals guide our approach. First, we want to gain detailed insights into what learners know at different points in their training. For example, rather than simply reporting on the proportions of questions participants answer correctly (i.e., their overall performance), we seek estimates of their knowledge about a variety of specific concepts. Second, we want our approach to be potentially scalable to large numbers of diverse concepts, courses, and students. This requires that the conceptual content of interest be discovered *automatically*, rather than relying on manually produced ratings or labels.

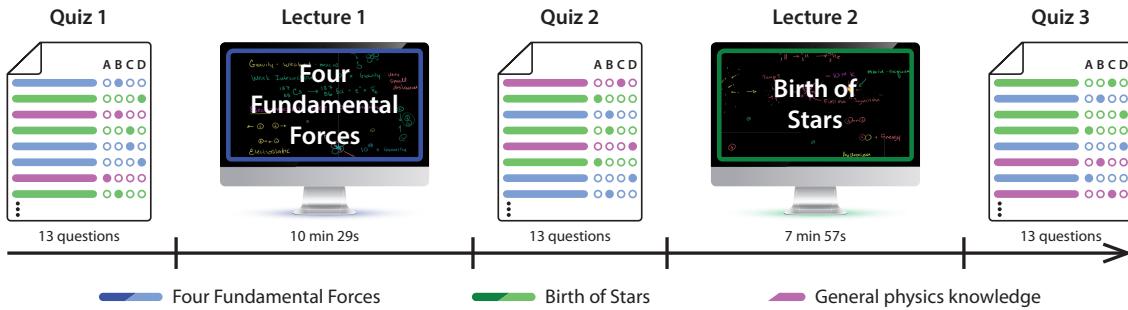


Figure 1: Experimental paradigm. Participants alternate between completing three 13-question multiple-choice quizzes and watching two Khan Academy lectures. Each quiz contains a mix of 5 questions about Lecture 1, 5 questions about Lecture 2, and 3 questions about general physics knowledge. The specific questions reflected on each quiz, and the orders of each quiz's questions, were randomized across participants.

127 We asked participants in our study to complete brief multiple-choice quizzes before, between,
 128 and after watching two lecture videos from the Khan Academy [31] platform (Fig. 1). The first
 129 lecture video, entitled *Four Fundamental Forces*, discussed the four fundamental forces in physics:
 130 gravity, strong and weak interactions, and electromagnetism. The second, entitled *Birth of Stars*,
 131 provided an overview of our current understanding of how stars form. We selected these particular
 132 lectures to satisfy three general criteria. First, we wanted both lectures to be accessible to a broad
 133 audience (i.e., with minimal prerequisite knowledge) so as to limit the impact of prior training
 134 on participants' abilities to learn from the lectures. To this end, we selected two introductory
 135 videos that were intended to be viewed at the start of students' training in their respective content
 136 areas. Second, we wanted the two lectures to have some related content, so that we could test
 137 our approach's ability to distinguish similar conceptual content. To this end, we chose two videos
 138 from the same Khan Academy course domain, "Cosmology and Astronomy." Third, we sought to
 139 minimize dependencies and specific overlap between the videos. For example, we did not want
 140 participants' abilities to understand one video to (directly) influence their abilities to understand the
 141 other. To satisfy this last criterion, we chose videos from two different lecture series (Lectures 1 and
 142 2 were from the "Scale of the Universe" and "Stars, Black Holes, and Galaxies" series, respectively).

143 We also wrote a set of multiple-choice quiz questions that we hoped would enable us to
 144 evaluate participants' knowledge about each individual lecture, along with related knowledge



Figure 2: Modeling course content. **A. Building a document pool from sliding windows of text.** We decompose each lecture’s transcript into a series of overlapping sliding windows. The full set of transcript snippets (across all windows) may be treated as a set of “documents” for training a text embedding model. **B. Constructing lecture content trajectories.** After training the model on the sliding windows from both lectures, we transform each lecture into a “trajectory” through text embedding space by joining the embedding coordinates of successive sliding windows parsed from its transcript. **C. Embedding multiple lectures and questions in a shared space.** We apply the same model (trained on the two lectures’ windows) to both lectures, along with the text of each question in our pool (Supp. Tab. 1), to project them into a shared text embedding space. This results in one trajectory per lecture and one coordinate for each question. Here, we have projected the 15-dimensional embeddings onto their first 3 principal components for visualization.

145 about physics concepts not specifically presented in either video (see Supp. Tab. 1 for the full list
 146 of questions in our stimulus pool). Participants answered questions randomly drawn from each
 147 content area (Lecture 1, Lecture 2, and general physics knowledge) on each of the three quizzes.
 148 Quiz 1 was intended to assess participants’ “baseline” knowledge before training, Quiz 2 assessed
 149 knowledge after watching the *Four Fundamental Forces* video (i.e., Lecture 1), and Quiz 3 assessed
 150 knowledge after watching the *Birth of Stars* video (i.e., Lecture 2).

151 To study in detail how participants’ conceptual knowledge changed over the course of the
 152 experiment, we first sought to model the conceptual content presented to them at each moment
 153 throughout each of the two lectures. We adapted an approach we developed in prior work [24]
 154 to identify the latent themes in the lectures using a topic model [6]. Briefly, topic models take
 155 as input a collection of text documents, and learn a set of “topics” (i.e., latent themes) from their
 156 contents. Once fit, a topic model can be used to transform arbitrary (potentially new) documents
 157 into sets of “topic proportions,” describing the weighted blend of learned topics reflected in their
 158 texts. We parsed automatically generated transcripts of the two lectures into overlapping sliding
 159 windows, where each window contained the text of the lecture transcript from a particular time

span. We treated the set of text snippets (across all of these windows) as documents to fit the model (Fig. 2A; see *Constructing text embeddings of multiple lectures and questions*). Transforming the text from every sliding window with the model yielded a number-of-windows by number-of-topics (15) topic-proportions matrix describing the unique mixture of broad themes from both lectures reflected in each window’s text. Each window’s “topic vector” (i.e., column of the topic-proportions matrix) is analogous to a coordinate in a 15-dimensional space whose axes are topics discovered by the model. Within this space, each lecture’s sequence of topic vectors (i.e., corresponding to its transcript’s overlapping text snippets across sliding windows) forms a *trajectory* that captures how its conceptual content unfolds over time (Fig. 2B). We resampled these trajectories to a resolution of one topic vector for each second of video (i.e., 1 Hz).

We hypothesized that a topic model trained on transcripts of the two lectures should also capture the conceptual knowledge probed by each quiz question. If indeed the topic model could capture information about the deeper conceptual content of the lectures (i.e., beyond surface-level details such as particular word choices), then we should be able to recover a correspondence between each lecture and questions *about* each lecture. Importantly, such a correspondence could not solely arise from superficial text matching between lecture transcripts and questions, since the lectures and questions often used different words (Supp. Fig. 5) and phrasings. Simply comparing the average topic weights from each lecture and question set (averaging across time and questions, respectively) reveals a striking correspondence (Supp. Fig. 2). Specifically, the average topic weights from Lecture 1 are strongly correlated with the average topic weights from Lecture 1 questions ($r(13) = 0.809$, $p < 0.001$, 95% confidence interval (CI) = [0.633, 0.962]), and the average topic weights from Lecture 2 are strongly correlated with the average topic weights from Lecture 2 questions ($r(13) = 0.728$, $p = 0.002$, 95% CI = [0.456, 0.920]). At the same time, the average topic weights from the two lectures are *negatively* correlated with [the average topic weights from](#) their non-matching question sets (Lecture 1 video vs. Lecture 2 questions: $r(13) = -0.547$, $p = 0.035$, 95% CI = [-0.812, -0.231]; Lecture 2 video vs. Lecture 1 questions: $r(13) = -0.612$, $p = 0.015$, 95% CI = [-0.874, -0.281]), indicating that the topic model also exhibits some degree of specificity. The full set of pairwise comparisons between average topic weights for the lectures and question sets



Figure 3: Lecture and question topic overlap. A. Topic weight variability. The bar plots display the variance of each topic's weight across lecture timepoints (top row) and questions (bottom row); colors denote topics. The top-weighted words from the most “expressive” (i.e., variable across observations) topic from each lecture are displayed in the upper right (orange: topic 2; yellow-green: topic 4). The top-weighted words from the full set of topics may be found in Supplementary Table 2. **B. Relationships between topic weight variability.** Pairwise correlations between the distributions of topic weight variance for each lecture and question set. Each row and column corresponds to a bar plot in Panel A.

188 is reported in Supplementary Figure 2.

189 Another, more sensitive, way of summarizing the conceptual content of the lectures and ques-
190 tions is to look at *variability* in how topics are weighted over time and across different questions
191 (Fig. 3). Intuitively, the variability in the expression of a given topic relates to how much “infor-
192 mation” [19] the lecture (or question set) reflects about that topic. For example, suppose a given
193 topic is weighted on heavily throughout a lecture. That topic might be characteristic of some
194 aspect or property of the lecture *overall* (conceptual or otherwise), but unless the topic’s weights
195 changed in meaningful ways over time, the topic would be a poor indicator of any *specific* concep-
196 tual content in the lecture. We therefore also compared the variances in topic weights (across time
197 or questions) between the lectures and questions. The variability in topic expression (over time
198 and across questions) was similar for the Lecture 1 video and questions ($r(13) = 0.824, p < 0.001,$
199 $95\% \text{ CI} = [0.696, 0.973]$) and the Lecture 2 video and questions ($r(13) = 0.801, p < 0.001, 95\%$
200 $\text{CI} = [0.539, 0.958]$). Simultaneously, as reported in Figure 3B, the variability variabilities in topic
201 expression across *different* videos and lecture-specific questions (i.e., Lecture 1 video vs. Lecture 2

202 questions; Lecture 2 video vs. Lecture 1 questions) were negatively correlated, and neither video's
203 topic variability was reliably correlated with the topic variability across general physics knowledge
204 questions. Taken together, the analyses reported in Figure 3 and Supplementary Figure 2 indicate
205 that a topic model fit to the videos' transcripts can also reveal correspondences (at a coarse scale)
206 between the lectures and questions.

207 While an individual lecture may be organized around a single broad theme at a coarse scale,
208 at a finer scale, each moment of a lecture typically covers a narrower range of content. Given
209 the correspondence we found between the **variability** **variabilities** in topic expression across mo-
210 ments of each lecture and questions from its corresponding set (Fig. 3), we wondered whether the
211 text embedding model might additionally capture these conceptual relationships at a finer scale.
212 For example, if a particular question asks about the content from one small part of a lecture, we
213 wondered whether the text embeddings could be used to automatically identify the "matching"
214 moment(s) in the lecture. To explore this, we computed the correlation between each question's
215 topic weights and the topic weights for each second of its corresponding lecture, and found that
216 each question appeared to be temporally specific (Fig. 4). In particular, most questions' topic
217 vectors were maximally correlated with a well-defined (and relatively narrow) range of time-
218 points from their corresponding lectures, and the correlations fell off sharply outside of that range
219 (Supp. Figs. 3, 4). We also qualitatively examined the best-matching intervals for each question by
220 comparing the question's text to the **text of transcribed text from** the most-correlated parts of the
221 lectures (Supp. Tab. 3). Despite that the questions were excluded from the text embedding model's
222 training set, in general we found (through manual inspection) a close correspondence between
223 the conceptual content that each question probed and the content covered by the best-matching
224 moments of the lectures. Two representative examples are shown at the bottom of Figure 4.

225 The ability to quantify how much each question is "asking about" the content from each moment
226 of the lectures could enable high-resolution insights into participants' knowledge. Traditional
227 approaches to estimating how much a student "knows" about the content of a given lecture entail
228 **administering some form of assessment (e.g., a quiz) and** computing the proportion of correctly
229 answered questions. But if two students receive identical scores on **such** an exam, might our



Figure 4: Which parts of each lecture are captured by each question? Each panel displays time series plots showing how each question’s topic vector correlates with each video timepoint’s topic vector (Panel A.: correlations for the *Four Fundamental Forces* lecture and associated questions; Panel B.: correlations for the *Birth of Stars* lecture and associated questions). The colors denote question identities. The diamonds in each panel denote the moment of peak correlation between the indicated question and the lecture trajectory. The associated questions’ text and snippets of the lectures’ transcripts from the surrounding 30 seconds, are displayed at the bottom of the figure.

modeling framework help us to gain more nuanced insights into the *specific* content that each student has mastered (or failed to master)? For example, a student who misses three questions that were all about the same concept (e.g., concept *A*) will have gotten the same *proportion* of questions correct as another student who missed three questions about three *different* concepts (e.g., *A*, *B*, and *C*). But if we wanted to help these two students fill in the “gaps” in their understandings, we might do well to focus specifically on concept *A* for the first student, but to also add in materials pertaining to concepts *B* and *C* for the second student. In other words, raw “proportion-correct” measures may capture *how much* a student knows, but not *what* they know. We wondered whether our modeling framework might enable us to (formally and automatically) infer participants’ knowledge at the scale of individual concepts (e.g., as captured by a single moment of a lecture).

We developed a simple formula (Eqn. 1) for using a participant’s responses to a small set of multiple-choice questions to estimate how much the participant “knows” about the concept reflected by any arbitrary coordinate \vec{x} in text embedding space (e.g., the content reflected by any

243 moment in a lecture they had watched; see *Estimating dynamic knowledge traces*). Essentially, the
244 estimated knowledge at coordinate x is given by the weighted ~~average~~ proportion of quiz questions
245 the participant answered correctly, where the weights reflect how much each question is “about”
246 the content at x . When we apply this approach to estimate the participant’s knowledge about the
247 content presented in each moment of each lecture, we can obtain a detailed time course describing
248 how much “knowledge” ~~the~~that participant has about the content presented at any part of the
249 lecture. As shown in Figure 5A and C, we can apply this approach separately for the questions
250 from each quiz participants took throughout the experiment. From just a few questions per quiz
251 (see *Estimating dynamic knowledge traces*), we obtain a high-resolution snapshot (at the time each
252 quiz was taken) of what the participants knew about any moment’s content, from either of the two
253 lectures they watched (comprising a total of 1,100 samples across the two lectures).

254 While the time courses in Figure 5A and C provide detailed *estimates* about participants’
255 knowledge, these estimates are of course only *useful* to the extent that they accurately reflect what
256 participants actually know. As one sanity check, we anticipated that the knowledge estimates
257 should reflect a content-specific “boost” in participants’ knowledge after watching each lecture. In
258 other words, if participants learn about each lecture’s content ~~when they watch each lecture upon~~
259 watching it, the knowledge estimates should capture that. After watching the *Four Fundamental*
260 *Forces* lecture, participants should exhibit more knowledge for the content of that lecture than they
261 had before, and that knowledge should persist for the remainder of the experiment. Specifically,
262 knowledge about that lecture’s content should be relatively low when estimated using Quiz 1
263 responses, but should increase when estimated using Quiz 2 or 3 responses (Fig. 5B). Indeed, we
264 found that participants’ estimated knowledge about the content of *Four Fundamental Forces* was
265 substantially higher on Quiz 2 versus Quiz 1 ($t(49) = 8.764, p < 0.001$) and on Quiz 3 versus Quiz 1
266 ($t(49) = 10.519, p < 0.001$). We found no reliable differences in estimated knowledge about that
267 lecture’s content on Quiz 2 versus 3 ($t(49) = 0.160, p = 0.874$). Similarly, we hypothesized (and
268 subsequently confirmed) that participants should show greater estimated knowledge about the
269 content of the *Birth of Stars* lecture after (versus before) watching it (Fig. 5D). Specifically, since
270 participants watched that lecture after taking Quiz 2 (but before Quiz 3), we hypothesized that their

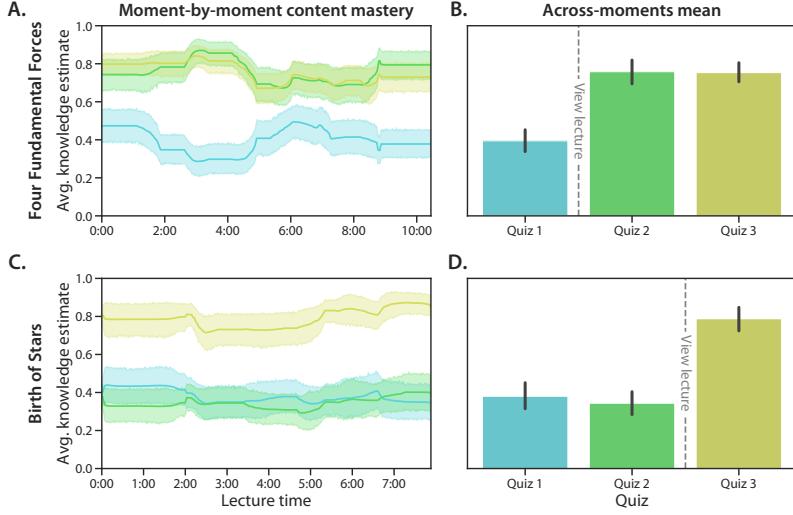


Figure 5: Estimating knowledge about the content presented at each moment of each lecture. **A. Knowledge about the time-varying content of *Four Fundamental Forces*.** Each trace displays the weighted proportion of correctly answered questions about the content reflected in each moment of the lecture (see *Estimating dynamic knowledge traces*), using responses from a single quiz (color). The traces are averaged across participants. **B. Average estimated knowledge about *Four Fundamental Forces*.** **C. Knowledge about the time-varying content of *Birth of Stars*.** The panel is in the same format as Panel A, but here the knowledge estimates are for the moment-by-moment content of the *Birth of Stars* lecture. **D. Average estimated knowledge about *Birth of Stars*.** The panel is in the same format as Panel B, but here the knowledge estimates are for the content of the *Birth of Stars* lecture. All panels: error ribbons and error bars denote 95% confidence intervals, estimated across participants.

knowledge estimates should be relatively low on Quizzes 1 and 2, but should show a “boost” on Quiz 3. Consistent with this prediction, we found no reliable differences in estimated knowledge about the *Birth of Stars* lecture content on Quizzes 1 versus 2 ($t(49) = 1.013, p = 0.316$), but the estimated knowledge was substantially higher on Quiz 3 versus 2 ($t(49) = 10.561, p < 0.001$) and Quiz 3 versus 1 ($t(49) = 8.969, p < 0.001$).

If we are able to accurately estimate a participant’s knowledge about the content tested by a given question, our estimates of their knowledge should carry some predictive information about whether ~~the participant is they are~~ likely to answer that question correctly or incorrectly. We developed a statistical approach to test this claim. For each ~~question~~ ~~quiz~~ ~~question a participant answered~~, in turn, we used Equation 1 to ~~predict each participant’s estimate their~~ knowledge at the given question’s embedding space coordinate ~~, using all other based on other~~ questions that participant answered on the same quiz. ~~For each~~ ~~We repeated this for all participants, and for each of the three quizzes. Then, separately for each quiz, we grouped these predicted knowledge values into two distributions: one for the predicted knowledge at the coordinates of correctly answered questions, and another for the predicted knowledge at the coordinates of incorrectly answered questions (Fig. 6). We then used Mann-Whitney U-tests to compare the means of these distributions of predicted knowledge~~ fit a generalized linear mixed model (GLMM) with a logistic link function to explain the likelihood of correctly answering a question as a function of estimated knowledge for its embedding coordinate, while accounting for random variation among participants and questions (see *GLMM METHODS SECTION PLACEHOLDER*). To assess the predictive value of the knowledge estimates, we compared each GLMMs to an analogous (i.e., nested) “null” model that did not consider estimated knowledge using parametric bootstrap likelihood-ratio tests.

We carried out ~~these analyses in three different ways. First, we used all (but one) of the questions from a given quiz (and participant) to predict knowledge at the embedding coordinate of a held-out question~~ three different versions of the analyses described above, wherein we considered different sources of information in our estimates of participants’ knowledge for each quiz question. First, we estimated knowledge at each question’s embedding coordinate using *all other questions answered by the same participant on the same quiz* (“All questions”~~in~~; Fig. 6, *top row*). This test was

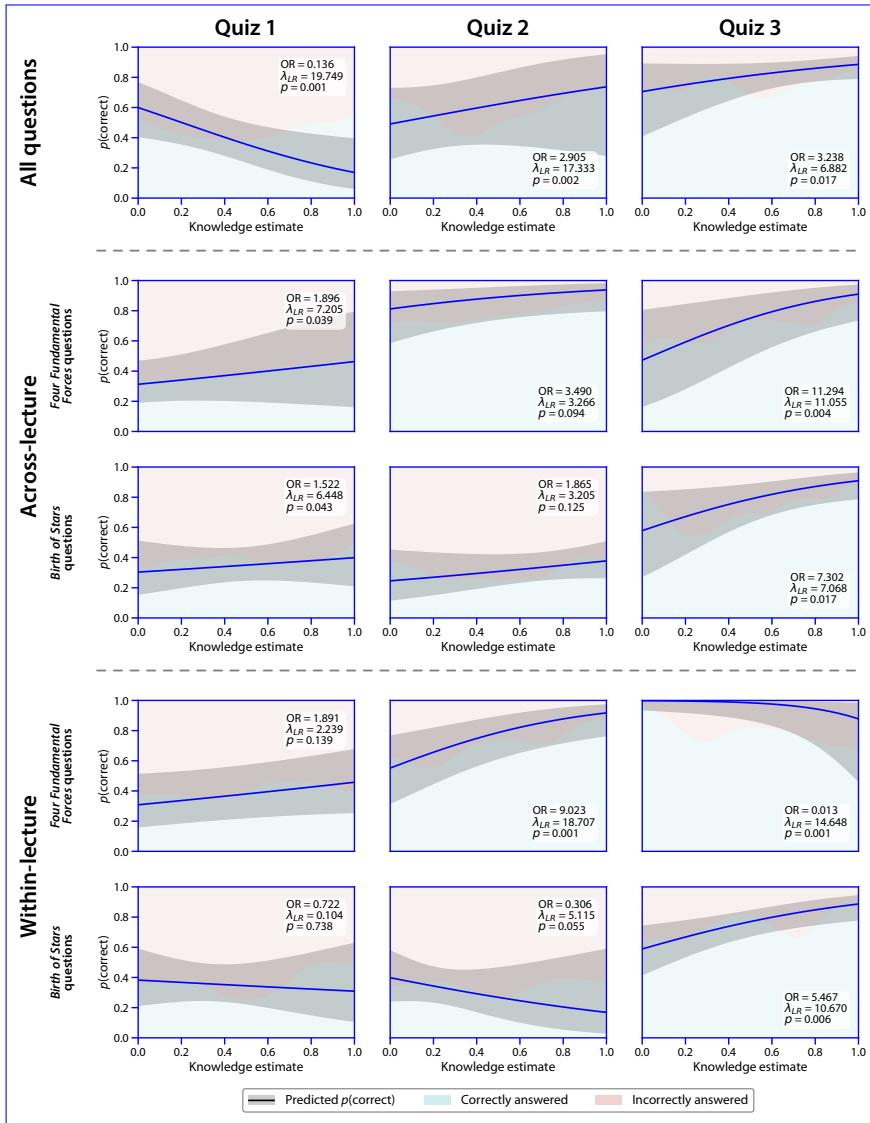


Figure 6: Predicting knowledge at the embedding coordinates of held-out questions. Predicting success on held-out questions using estimated knowledge. We used generalized linear mixed models (GLMMs) to model the likelihood of correctly answering a quiz question as a function of estimated knowledge for its embedding coordinate (see GLMM METHODS SECTION PLACEHOLDER). Separately for each quiz (column), we plot the distributions examined this relationship based on three different sets of predicted knowledge at the embedding coordinates of estimates: knowledge for each held-out correctly (blue) or incorrectly (red) answered question. The Mann-Whitney U tests reported in each panel are between based on all other questions the distributions of predicted knowledge at the coordinates of correctly and incorrectly same participant answered held-out questions. In on the top row same quiz ("All questions"; top row), we used all quiz questions (from each quiz, knowledge for each participant) except one to predict knowledge at the held-out question's embedding coordinate. In the middle rows ("Across-lecture"), we used all questions about one lecture to predict knowledge at based on all questions (from the embedding coordinate of a held-out question same participant and quiz) about the other lecture. In the bottom row ("Within-lecture"; middle rows), we used all but one and knowledge for each question about one lecture to predict knowledge at based on all other questions (from the embedding coordinate of a held-out question same participant and quiz) about the same lecture ("Within-lecture"; bottom rows). We repeated each of these analyses using all possible held-out questions for each quiz and participant. The arrows at the tops of background in each panel indicate whether displays the average predicted knowledge was higher for held-out kernel density estimates of the relative observed proportions of correctly answered (left blue) or versus incorrectly answered (right red) answered questions, for each level of estimated knowledge along the x-axis. The black curves display the (population-level) GLMM-predicted probabilities of correctly answering a question as a function of estimated knowledge. Error ribbons denote bootstrap-estimated 95% confidence intervals. JRM NOTE: RE-ORDER ROWS TO MATCH THE TEXT, AND UPDATE CAPTION ACCORDINGLY

intended to serve as an overall baseline for the assess the overall predictive power of our approach. Second, we used questions about one lecture to predict knowledge at the embedding coordinate of a held-out question about the other lecture, estimated knowledge for each question about a given lecture using only the other questions (from the same quiz and participant (“Across-lecture” in participant and quiz) about that same lecture (“Within-lecture”; Fig. 6, middle rows). This test was intended to test the assess the generalizability specificity of our approach by asking whether our knowledge predictions held across the content areas of the two lectures predictions could distinguish between questions about different content covered by the same lecture. Third, we used questions about one lecture to predict knowledge at the embedding coordinate of a held-out question about the same lecture, estimated knowledge for each question about one lecture using only questions (from the same quiz and participant (“Within-lecture” in participant and quiz) about the other lecture (“Across-lecture”; Fig. 6, bottom rows). This test was intended to test the assess the specificity generalizability of our approach by asking whether our knowledge predictions could distinguish between questions about different content covered by the same lecture. We repeated each of these analyses using all possible held-out questions for each quiz and participant. predictions held across the content areas of the two lectures.

For the initial quizzes participants took (prior to watching either lecture), predicted knowledge tended to be low overall, and relatively unstructured (Fig. 6, left column). When we held out individual questions and predicted their knowledge at the held-out questions’ embedding coordinates, we found no reliable differences in the predictions when the In performing these analyses, our null hypothesis is that the knowledge estimates we compute based on the quiz questions’ embedding coordinates do not provide useful information about participants’ abilities to answer those questions. What result might we expect to see if this is the case? To gain an intuition for this possibility, consider the expected outcome if we carried out these same analyses using a simple proportion-correct measure in lieu of our knowledge estimates. Suppose a participant correctly answered n out of q questions on a given quiz. If we hold out a single correctly answered question, the proportion of remaining questions answered correctly would be $\frac{n-1}{q-1}$. If we hold out a single incorrectly answered question, the proportion of remaining questions answered correctly

327 would be $\frac{n}{q-1}$. In this way, the proportion of correctly answered remaining questions is always
328 lower when the held-out question had been correctly versus incorrectly answered. This “null” effect
329 persisted when we used all of the Quiz 1 questions from a given participant to predict a held-out
330 question (“All questions”; $U = 50587$, $p = 0.723$), when we used questions from one lecture to
331 predict knowledge at the embedding coordinate of a question was answered correctly than when
332 it was answered incorrectly. Because our knowledge estimates are computed as a weighted
333 version of this same proportion-correct score (where each held-in question’s weight reflects its
334 embedding-space distance from the held-out question about the other lecture (“Across-lecture”;
335 predicting knowledge for question; see Eqn. 1), if these weights were uninformative (e.g., randomly
336 distributed), then we should expect to see this same inverse relationship between estimated
337 knowledge and performance, on average. On the other hand, if the spatial relationships among
338 the quiz questions’ embeddings are predictive of participants’ knowledge about the questions’
339 content, then we would expect higher estimated knowledge for held-out *Four Fundamental Forces*
340 Questions using *Birth of Stars* questions: $U = 8244$, $p = 0.184$; predicting knowledge for held-out
341 *Birth of Stars* questions: $U = 8202.5$, $p = 0.161$), and when we used questions from one lecture to
342 predict correctly (versus incorrectly) answered questions.

343 Before presenting our results, it is worth considering three possible explanations of why a
344 participant might answer a given question correctly or incorrectly. One possibility is that the
345 participant simply guessed the answer. A second is that they selected an answer by mistake, despite
346 “knowing” the correct answer. In both of these scenarios, the participant’s knowledge about the
347 question’s content should be uninformative about their observed response. A third possibility is
348 that the participant’s response reflects their *actual* knowledge about the question’s content. In this
349 case, we might expect to see a positive relationship between the participant’s knowledge and their
350 likelihood of answering the question correctly. However, in order to see this positive relationship,
351 the participant’s knowledge must be structured in a way that is reflected (at least partially) by the
352 embedding space. In other words, if the participant’s performance reflects their true knowledge,
353 but our text embedding space does not sufficiently capture the structure of that knowledge, then
354 the knowledge estimates we generate will not be predictive of the participant’s performance. In the

355 extreme, if the embedding space is completely unstructured with respect to the content of the quiz
356 questions, then we would expect to see the negative relationship between estimated knowledge
357 and performance that we described above.

358 When we fit a GLMM to estimates of participants' knowledge for each Quiz 1 question based
359 on all other Quiz 1 questions, we observed an outcome consistent with our null hypothesis:
360 higher estimated knowledge at the embedding coordinate of a held-out question about the
361 same lecture ("Within lecture"; *Four Fundamental Forces*: $U = 7681.5, p = 0.746$; *Birth of Stars*:
362 $U = 8125, p = 0.204$). We believe that this reflects a floor effect: when knowledge is low everywhere,
363 there is little signal to differentiate between what is known versus unknown. was associated with
364 a lower likelihood of answering the question correctly (odds ratio (*OR*) = 0.136, likelihood-ratio
365 test statistic (λ_{LR}) = 19.749, 95% CI = [14.352, 26.545], $p = 0.001$). This outcome suggests that our
366 knowledge estimates do not provide useful information about participants' Quiz 1 performance
367 when we aggregated across all question content areas. We speculated that this might either
368 indicate that the knowledge estimates are uninformative in general, or about Quiz 1 performance
369 in particular. This would be expected, for example, if participants were guessing about the answers
370 to the Quiz 1 questions (prior to having watched either lecture). When we repeated this analysis for
371 Quizzes 2 and 3, we found that higher estimated knowledge for a given question predicted a greater
372 likelihood of answering it correctly (Quiz 2: *OR* = 2.905, $\lambda_{LR} = 17.333$, 95% CI = [14.966, 29.309], $p = 0.002$;
373 Quiz 3: *OR* = 3.238, $\lambda_{LR} = 6.882$, 95% CI = [6.228, 8.184], $p = 0.017$). Taken together, these results
374 suggest that our knowledge estimates reliably predict participants' performance on individual
375 held-out quiz questions, but only after participants have received at least some training.

376 After watching *Four Fundamental Forces*, predicted knowledge for We observed a similar pattern
377 of results when used this approach to estimate participants' knowledge about held-out questions
378 that were answered correctly (from the second quiz; Fig. 6, middle column) exhibited a significant
379 positive shift relative to held-out questions that were answered incorrectly. This held when
380 we included all questions in the analysis ($U = 58332, p < 0.001$), when we predicted knowledge
381 across lectures (*Four Fundamental Forces*: $U = 6749.5, p = 0.014$; *Birth of Stars*: $U = 8480, p = 0.016$),
382 and when we predicted knowledge at the questions from one lecture using their performance on

383 other questions from the same lecture. Specifically, for Quiz 1 questions (i.e., prior to watching
384 either), participants' estimated knowledge for the embedding coordinates of held-out *Four Fundamental Forces*
385 questions-related questions estimated using other *Four Fundamental Forces* questions
386 from the same quiz and participant ($U = 7224, p < 0.001$). This difference did not hold for -related
387 questions did not reliably predict whether those questions were answered correctly ($OR = 1.891, \lambda_{LR} = 2.293, 95\% CI = [$
388 The same was true of knowledge estimates for held-out *Birth of Stars*-related questions based on
389 other *Birth of Stars*-related questions ($OR = 0.722, \lambda_{LR} = 5.115, 95\% CI = [0.094, 0.146], p = 0.738$).
390 As in our analysis that included all questions, we speculate that these "null" results might reflect
391 some degree of random guessing on Quiz 1. When we repeated these within-lecture knowledge
392 predictions at knowledge at embedding space coordinates of analyses using questions from Quiz 2
393 (which participants took immediately after viewing *Four Fundamental Forces* but prior to viewing
394 *Birth of Stars* questions), we found that they now reliably predicted success on *Four Fundamental*
395 *Forces*-related questions ($OR = 9.023, \lambda_{LR} = 18.707, 95\% CI = [10.877, 22.222], p = 0.001$) but not
396 on *Birth of Stars*-related questions ($U = 7419, p = 0.739$). Again, we suggest that this might reflect
397 a floor effect whereby, at that point in the participants' training, their knowledge about the
398 content of the $OR = 0.306, \lambda_{LR} = 5.115, 95\% CI = [4.624, 5.655], p = 0.055$). Here, we speculate
399 that participants might have been guessing about the *Birth of Stars* material is relatively low
400 everywhere in that region of text embedding space.

401 Finally, after watching *Birth of Stars*, predicted knowledge for held-out correctly answered
402 questions (from the third quiz; Fig. 6, right column) was higher than for held-out incorrectly
403 answered questions. This held when we included all questions in the analysis ($U = 38279, p = 0.022$),
404 when we carried out across-lecture predictions (content (e.g., prior to having watched it), whereas
405 they might have been drawing on some structured knowledge about the *Four Fundamental Forces*:
406 $U = 6684.5, p = 0.032$; content (e.g., from having just watched it). When we applied this approach
407 to Quiz 3 responses (given immediately after viewing *Birth of Stars*: $U = 6414.5, p = 0.002$), and
408 and when we carried out), we found that within-lecture knowledge predictions for held-out
409 estimates for *Birth of Stars* questions using other *Birth of Stars* questions from the same quiz and
410 participant ($U = 6126, p = 0.006$ -related questions could now reliably predict success on those

411 questions ($OR = 5.467$, $\lambda_{LR} = 10.670$, 95% CI = [7.998, 12.532], $p = 0.006$). However, we found the
412 opposite effect when we carried out within-lecture knowledge predictions for held-out estimates
413 for Four Fundamental Forces questions using other Four Fundamental Forces questions from the
414 same quiz and participant ($U = 6734$, $p = 0.027$). Specifically, on Quiz answered on Quiz 3,
415 our knowledge predictions for held-out correctly answered questions about Four Fundamental
416 Forces were reliably lower than those for their incorrectly answered counterparts. were no longer
417 directly related to the likelihood of successfully answering them and instead exhibited the inverse
418 relationship we would expect to arise from unstructured knowledge (with respect to the embedding
419 space; $OR = 0.013$, $\lambda_{LR} = 14.648$, 95% CI = [10.695, 23.096], $p = 0.001$). Speculatively, we suggest
420 that this may reflect participants forgetting some of the Four Fundamental Forces content (e.g.,
421 perhaps in favor of prioritizing encoding the just-watched Birth of Stars content in preparation for
422 the third quiz). If this forgetting happens in a relatively “random” way (with respect to spatial
423 distance within the text-embedding space), then it could explain why some held-out questions
424 about Four Fundamental Forces were answered incorrectly, even if questions at nearby coordinates
425 (i.e., about similar content) were answered correctly. This might lead our approach to over-estimate
426 knowledge for held-out questions about “forgotten” knowledge that participants answered incor-
427 rectly. Taken together, the results in Figure 6 indicate these within-lecture results suggest that
428 our approach can reliably predict acquired knowledge (especially about recently learned content)
429 , and distinguish between questions about different content covered by a single lecture when
430 participants have sufficiently structured knowledge about its contents, though this specificity may
431 decrease with time since the relevant material was learned.

432 Finally, we used this approach to estimate participants’ knowledge about held-out questions
433 from one lecture using their performance on other questions from the other lecture. Here we again
434 observed a similar pattern of results, though with some notable differences. On Quiz 1, we found
435 that participants’ abilities to correctly answer questions about Four Fundamental Forces could be
436 predicted from their responses to questions about Birth of Stars ($OR = 1.896$, $\lambda_{LR} = 7.205$, 95% CI = [6.224, 7.524], $p = 0.000$)
437 and similarly, that their ability to correctly answer Birth of Stars-related questions could be predicted
438 from their responses to Four Fundamental Forces-related questions ($OR = 1.522$, $\lambda_{LR} = 6.448$, 95% CI = [5.656, 6.843], $p = 0.000$).

Given the results from our analyses that included all questions and within-lecture predictions, we were surprised to find that the knowledge predictions are generalizable across the content areas spanned by the two lectures, while also specific enough to estimates could reliably (if weakly) predict participants' performance across content from different lectures. It is possible that this result reflects a combination of random guessing prior to training (leading to a weak effect size), in combination with some coarse-scale structured knowledge that participants had about the content prior to watching either lecture. When we repeated this analysis using questions from Quiz 2, we found participants' responses to *Four Fundamental Forces*-related questions did not reliably predict their success on *Birth of Stars*-related questions ($OR = 1.865, \lambda_{LR} = 3.205, 95\% CI = [3.027, 3.600], p = 0.125$), nor did their responses to *Birth of Stars*-related questions reliably predict their success on *Four Fundamental Forces*-related questions ($OR = 3.490, \lambda_{LR} = 3.266, 95\% CI = [3.033, 3.866], p = 0.094$). These "prediction failures" appear to come from the fact that any signal derived from participants' knowledge about the content of the *Birth of Stars* lecture (prior to watching it) is swamped by the much more dramatic increase in their knowledge about the content of the *Four Fundamental Forces* (which they watched just prior to taking Quiz 2). This is reflected in their Quiz 2 performance for questions about each lecture (mean proportion correct for *Four Fundamental Forces*-related questions on Quiz 2: 0.77; mean proportion correct for *Birth of Stars*-related questions on Quiz 2: 0.36). When we again carried out these across-lecture knowledge predictions using questions from Quiz 3 (when participants had now viewed both lectures), we could again reliably predict success on questions about both *Four Fundamental Forces* ($OR = 11.294, \lambda_{LR} = 11.055, 95\% CI = [9.126, 18.476], p = 0.004$) and *Birth of Stars* ($OR = 7.302, \lambda_{LR} = 7.068, 95\% CI = [6.490, 8.584], p = 0.017$) using responses to questions about the other lecture's content. Across all three versions of these analyses, our results suggest that (by and large) our knowledge estimations can reliably predict participants' abilities to answer individual quiz questions, distinguish between questions about more subtly different content within the same lecture similar content, and generalize across content areas, provided that participants' quiz responses reflect a minimum level of "real" knowledge about both content on which these predictions are based and that for which they are made. Our results also indicate some important limitations of our approach: if participants' quiz performance does

467 not reflect what they know (e.g., when they “guess”), or if their knowledge is not structured in a
468 way that is reflected by the embedding space, then our knowledge estimates will not be predictive
469 of their performance.

470 That the knowledge predictions derived from the text embedding space reliably distinguish
471 between held-out correctly versus incorrectly answered questions (Fig. 6) suggests that spatial
472 relationships within this space can help explain what participants know. But how far does this
473 explanatory power extend? For example, suppose we know that a participant correctly answered a
474 question at embedding coordinate x . As we move farther away from x in the embedding space, how
475 does the likelihood that the participant knows about the content at a given location “fall off” with
476 distance? Conversely, suppose the participant instead answered that same question *incorrectly*.
477 Again, as we move farther away from x in the embedding space, how does the likelihood that the
478 participant does *not* know about a coordinate’s content change with distance? We reasoned that,
479 assuming our embedding space is capturing something about how individuals actually organize
480 their knowledge, a participant’s ability to answer questions embedded very close to x should
481 tend to be similar to their ability to answer the question embedded *at* x . Whereas at another
482 extreme, once we reach some sufficiently large distance from x , our ability to infer whether or
483 not a participant will correctly answer a question based on their ability to answer the question
484 at x should be no better than guessing based on their *overall* proportion of correctly answered
485 questions. In other words, beyond the maximum distance at which the participant’s ability to
486 answer the question at x is informative of their ability to answer a second question at location y ,
487 then guessing the outcome at y based on x should be no more successful than guessing based on a
488 measure that does not consider embedding space distance.

489 With these ideas in mind, we asked: conditioned on answering a question correctly, what
490 proportion of all questions (within some radius, r , of that question’s embedding coordinate)
491 were answered correctly? We plotted this proportion as a function of r . Similarly, we could
492 ask, conditioned on answering a question incorrectly, how the proportion of correct responses
493 changed with r . As shown in Figure 7, we found that quiz performance falls off smoothly with
494 distance, and the “rate” of the falloff does not appear to change across the different quizzes, as

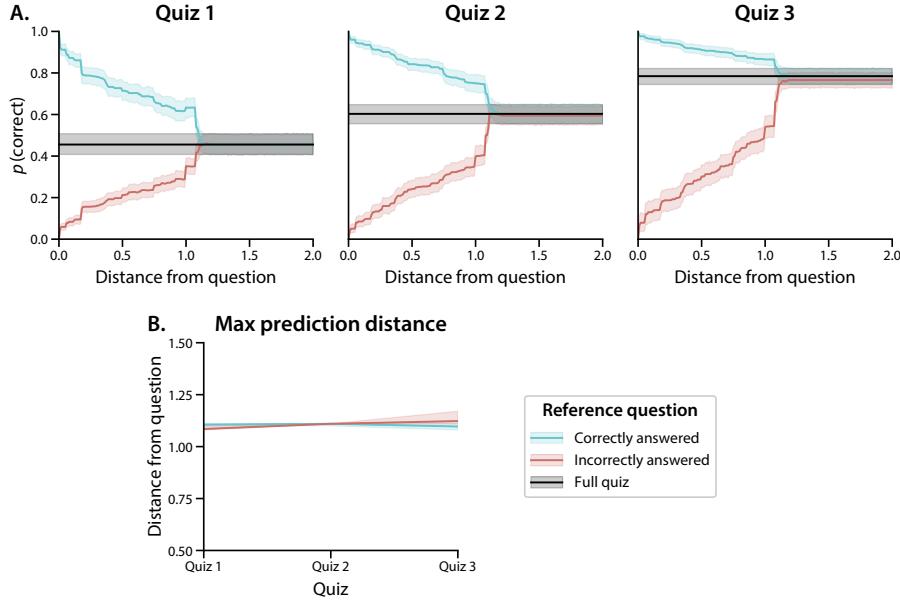


Figure 7: Knowledge falls off gradually in text embedding space. A. Performance versus distance. For each participant, for each correctly answered question (blue) or incorrectly answered question (red), we computed the proportion of correctly answered questions within a given distance of that question’s embedding coordinate. We used these proportions as a proxy for participants’ knowledge about the content within that region of the embedding space. We repeated this analysis for all questions and participants, and separately for each quiz (column). The black lines denote the average proportion correct across *all* questions included in the analysis at the given distance. **B. Maximum distance for which performance is reliably different from the average.** We used a bootstrap procedure (see *Estimating the “smoothness” of knowledge*) to estimate the point at which the blue and red lines in Panel A reliably diverged from the black line. We repeated this analysis separately for correctly and incorrectly answered questions from each quiz. **All panels.** Error ribbons denote bootstrap-estimated 95% confidence intervals.

measured by the distance at which performance becomes statistically indistinguishable from a simple proportion correct score (see *Estimating the “smoothness” of knowledge*). This suggests that, at least within the region of text embedding space covered by the questions our participants answered (and as characterized using our topic model), the rate at which knowledge changes with distance is relatively constant, even as participants’ overall level of knowledge varies across quizzes or regions of the embedding space.

Knowledge estimates need not be limited to the content of the lectures. As illustrated in Figure 8, our general approach to estimating knowledge from a small number of quiz questions may be extended to *any* content, given its text embedding coordinate. To visualize how knowledge

504 “spreads” through text embedding space to content beyond the lectures participants watched, we
505 first fit a new topic model to the lectures’ sliding windows with $k = 100$ topics. Conceptually,
506 increasing the number of topics used by the model functions to increase the “resolution” of the
507 embedding space, providing a greater ability to estimate knowledge for content that is highly
508 similar to (but not precisely the same as) that contained in the two lectures. We note that we
509 used these 2D maps solely for visualization; all relevant comparisons, distance computations, and
510 statistical tests we report above were carried out in the original 15-dimensional space, using the
511 15-topic model. Aside from increasing the number of topics from 15 to 100, all other procedures
512 and model parameters were carried over from the preceding analyses. As in our other analyses,
513 we resampled each lecture’s topic trajectory to 1 Hz and projected each question into a shared text
514 embedding space.

515 We projected the resulting 100-dimensional topic vectors (for each second of video and each quiz
516 question) onto a shared 2-dimensional plane (see *Creating knowledge and learning map visualizations*).
517 Next, we sampled points from a 100×100 grid of coordinates that evenly tiled a rectangle enclos-
518 ing the 2D projections of the videos and questions. We used Equation 4 to estimate participants’
519 knowledge at each of these 10,000 sampled locations, and averaged these estimates across par-
520 ticipants to obtain an estimated average *knowledge map* (Fig. 8A). Intuitively, the knowledge map
521 constructed from a given quiz’s responses provides a visualization of how “much” participants
522 knew about any content expressible by the fitted text embedding model at the point in time when
523 they completed that quiz.

524 Several features of the resulting knowledge maps are worth noting. The average knowledge
525 map estimated from Quiz 1 responses (Fig. 8A, leftmost map) shows that participants tended to
526 have relatively little knowledge about any parts of the text embedding space (i.e., the shading is
527 relatively dark everywhere). The knowledge map estimated from Quiz 2 responses shows a marked
528 increase in knowledge on the left side of the map (around roughly the same range of coordinates
529 traversed by the *Four Fundamental Forces* lecture, indicated by the dotted blue line). In other words,
530 participants’ estimated increase in knowledge is localized to conceptual content that is nearby (i.e.,
531 related to) the content from the lecture they watched prior to taking Quiz 2. This localization is

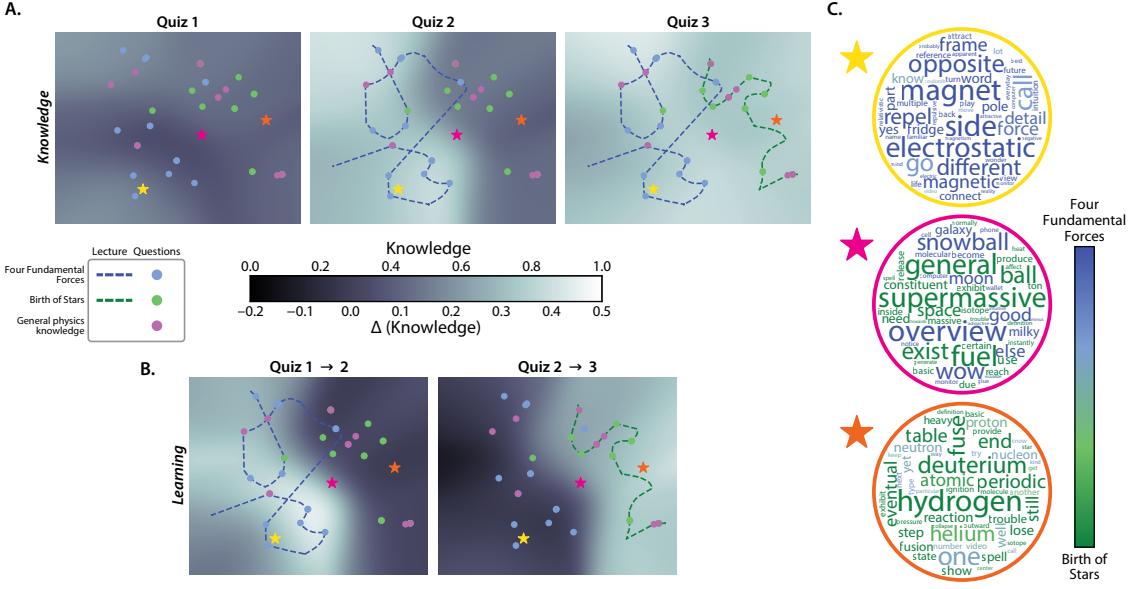


Figure 8: Mapping out the geometry of knowledge and learning. **A.** Average “knowledge maps” estimated using each quiz. Each map displays a 2D projection of the estimated knowledge about the content reflected by *all* regions of topic space (see *Creating knowledge and learning map visualizations*). The topic trajectories of the two lectures are indicated by dotted lines (blue: Lecture 1; green: Lecture 2), and the coordinates of each question are indicated by dots (light blue: Lecture 1-related; light green: Lecture 2-related; purple: general physics knowledge). Each map reflects an average across all participants. For individual participants’ maps, see Supplementary Figures 7, 8, and 9. **B.** Average “learning maps” estimated between each successive pair of quizzes. The learning maps follow the same general format as the knowledge maps in Panel A, but here the shading at each coordinate indicates the *difference* between the corresponding coordinates in the indicated pair of knowledge maps—i.e., how much the estimated knowledge “changed” between the two quizzes. Each map reflects an average across all participants. For individual participants’ maps, see Supplementary Figures 10 and 11. **C.** Word clouds for sampled points in topic space. Each word cloud displays the weighted blend of words underlying the topic proportions represented at the corresponding colored star’s location on the maps. In each word cloud, the words’ relative sizes correspond to their relative weights at the starred location, and their colors indicate their relative weights in *Four Fundamental Forces* (blue) versus *Birth of Stars* (green) lectures, on average, across all timepoints’ topic vectors.

532 non-trivial: these knowledge estimates are informed only by the embedded coordinates of the
533 *quiz questions*, not by the embeddings of either lecture (see Eqn. 4). Finally, the knowledge map
534 estimated from Quiz 3 responses shows a second increase in knowledge, localized to the region
535 surrounding the embedding of the *Birth of Stars* lecture participants watched immediately prior to
536 taking Quiz 3.

537 Another way of visualizing these content-specific increases in knowledge after participants
538 viewed each lecture is displayed in Figure 8B. Taking the point-by-point difference between the
539 knowledge maps estimated from responses to a successive pair of quizzes yields a *learning map*
540 that describes the *change* in knowledge estimates from one quiz to the next. These learning maps
541 highlight that the estimated knowledge increases we observed across maps were specific to the
542 regions around the embeddings of each lecture, in turn.

543 Because the 2D projection we used to construct the knowledge and learning maps is invertible,
544 we may gain additional insights into these maps' meanings by reconstructing the original high-
545 dimensional topic vector for any location on the map we are interested in. For example, this could
546 serve as a useful tool for an instructor looking to better understand which content areas a student
547 (or a group of students) knows well (or poorly). As a demonstration, we show the top-weighted
548 words from the blends of topics reconstructed from three example locations on the maps (Fig. 8C):
549 one point near the *Four Fundamental Forces* embedding (yellow), a second point near the *Birth of*
550 *Stars* embedding (orange), and a third point between the two lectures' embeddings (pink). As
551 shown in the word clouds in the panel, the top-weighted words at the example coordinate near the
552 *Four Fundamental Forces* embedding tended to be weighted more heavily by the topics expressed
553 in that lecture. Similarly, the top-weighted words at the example coordinate near the *Birth of Stars*
554 embedding tended to be weighted more heavily by the topics expressed in *that* lecture. And the
555 top-weighted words at the example coordinate between the two lectures' embeddings show a
556 roughly even mix of words most strongly associated with each lecture.

557 **Discussion**

558 We developed a computational framework that uses short multiple-choice quizzes to gain nuanced
559 insights into what learners know and how their knowledge changes with training. First, we show
560 that our approach can automatically match the conceptual knowledge probed by individual quiz
561 questions to the corresponding moments in lecture videos when those concepts were presented
562 (Fig. 4). Next, we demonstrate how we can estimate moment-by-moment “knowledge traces”
563 that reflect the degree of knowledge participants have about each video’s time-varying content,
564 and capture temporally specific increases in knowledge after viewing each lecture (Fig. 5). We
565 also show that these knowledge estimates can generalize to held-out questions (Fig. 6). Finally,
566 we use our framework to construct visual maps that provide snapshot estimates of how much
567 participants know about any concept within the scope of our text embedding model, and how
568 much their knowledge of those concepts changes with training (Fig. 8).

569 We view our work as making several contributions to the study of how people acquire con-
570 ceptual knowledge. First, from a methodological standpoint, our modeling framework provides
571 a systematic means of mapping out and characterizing knowledge in maps that have infinite (ar-
572 bitrarily many) numbers of coordinates, and of “filling out” those maps using relatively small
573 numbers of multiple choice quiz questions. Our experimental finding that we can use these maps
574 to predict responses to held-out questions has several psychological implications as well. For ex-
575 ample, concepts that are assigned to nearby coordinates by the text embedding model also appear
576 to be “known to a similar extent” (as reflected by participants’ responses to held-out questions;
577 Fig. 6). This suggests that participants also *conceptualize* similarly the content reflected by nearby
578 embedding coordinates. **The “spatial smoothness” of How participants’ knowledge (as estimated
579 using quiz performance) is being falls off with spatial distance is** captured by the knowledge maps
580 we **are inferring infer** from their quiz responses (e.g., Figs. 7, 8). In other words, our study shows
581 that knowledge about a given concept implies knowledge about related concepts, and we also
582 show how estimated knowledge falls off with distance in text embedding space.

583 In our study, we characterize the “coordinates” of participants’ knowledge using a relatively

simple “bag of words” text embedding model [LDA; 6]. More sophisticated text embedding models, such as transformer-based models [15, 47, 58, 61] can learn complex grammatical and semantic relationships between words, higher-order syntactic structures, stylistic features, and more. We considered using transformer-based models in our study, but we found that the text embeddings derived from these models were surprisingly uninformative with respect to differentiating or otherwise characterizing the conceptual content of the lectures and questions we used. We suspect that this reflects a broader challenge in constructing models that are high-resolution within a given domain (e.g., the domain of physics lectures and questions) *and* sufficiently broad so as to enable them to cover a wide range of domains. For example, we found that the embeddings derived even from much larger and more modern models like BERT [15], GPT [61], LLaMa [58], and others that are trained on enormous text corpora, end up yielding poor resolution within the content space spanned by individual course videos (Supp. Fig. 6). Whereas the LDA embeddings of the lectures and questions are “near” each other (i.e., the convex hull enclosing the two lectures’ trajectories is highly overlapping with the convex hull enclosing the questions’ embeddings), the BERT embeddings of the lectures and questions are instead largely distinct (top row of Supp. Fig. 6). The LDA embeddings of the questions for each lecture and the corresponding lecture’s trajectory are also similar. For example, as shown in Fig. 2C, the LDA embeddings for *Four Fundamental Forces* questions (blue dots) appear closer to the *Four Fundamental Forces* lecture trajectory (blue line), whereas the LDA embeddings for *Birth of Stars* questions (green dots) appear closer to the *Birth of Stars* lecture trajectory (green line). The BERT embeddings of the lectures and questions do not show this property (Supp. Fig. 6). We also examined per-question “content matches” between individual questions and individual moments of each lecture (Figs. 4, 6). The time series plot of individual questions’ correlations are different from each other when computed using LDA (e.g., the traces can be clearly visually separated), whereas the correlations computed from BERT embeddings of different questions all look very similar. This tells us that LDA is capturing some differences in content between the questions, whereas BERT is not. The time series plots of individual questions’ correlations have clear “peaks” when computed using LDA, but not when computed using BERT. This tells us that LDA is capturing a “match” between the content of each question and a

612 relatively well-defined time window of the corresponding lectures. The BERT embeddings appear
613 to blur together the content of the questions versus specific moments of each lecture. Finally, we
614 also compared the pairwise correlations between embeddings of questions within versus across
615 content areas (i.e., content covered by the individual lectures, lecture-specific questions, and by the
616 “general physics knowledge” questions). The LDA embeddings show a strong contrast between
617 same-content embeddings versus across-content embeddings. In other words, the embeddings of
618 questions about the *Four Fundamental Forces* material are highly correlated with the embeddings of
619 the *Four Fundamental Forces* lecture, but not with the embeddings of *Birth of Stars*, questions about
620 *Birth of Stars*, or general physics knowledge questions. We see a similar pattern with the LDA
621 embeddings of the *Birth of Stars* questions (Fig. 3, Supp. Fig. 2). In contrast, the BERT embeddings
622 are all highly correlated with each other (Supp. Fig. 6). Taken together, these comparisons illus-
623 trate how LDA (trained on the specific content in question) provides both coverage of the requisite
624 material and specificity at the level of the content covered by individual questions. BERT, on the
625 other hand, essentially assigns both lectures and all of the questions (which are all broadly about
626 “physics”) into a tiny region of its embedding space, thereby blurring out meaningful distinctions
627 between different specific concepts covered by the lectures and questions. We note that these are
628 not criticisms of BERT (or other large language models trained on large and diverse corpora).
629 Rather, our point is that simple fine-tuned models trained on a relatively small but specialized
630 corpus can outperform much more complicated models trained on much larger corpora, when we
631 are specifically interested in capturing subtle conceptual differences at the level of a single course
632 lecture or question. Of course if our goal had been to find a model that generalized to many
633 different content areas, we would expect our approach to perform comparatively poorly relative to
634 BERT or other much larger models. We suggest that bridging the tradeoff between high resolution
635 within each content area versus the ability to generalize to many different content areas will be an
636 important challenge for future work in this domain.

637 Another application for large language models that does *not* require explicitly modeling the
638 content of individual lectures or questions is to leverage the models’ abilities to generate text. For
639 example, generative text models like ChatGPT [47] and LLaMa [58] are already being used to build

640 a new generation of interactive tutoring systems [e.g., 38]. Unlike the approach we have taken here,
641 these generative text model-based systems do not explicitly model what learners know, or how
642 their knowledge changes over time with training. One could imagine building a hybrid system
643 that combines the best of both worlds: a large language model that can *generate* text, combined
644 with a smaller model that can *infer* what learners know and how their knowledge changes over
645 time. Such a hybrid system could potentially be used to build the next generation of interactive
646 tutoring systems that are able to adapt to learners' needs in real time, and that are able to provide
647 more nuanced feedback about what learners know and what they do not know.

648 At the opposite end of the spectrum from large language models, one could also imagine
649 *simplifying* some aspects of our LDA-based approach by computing simple word overlap metrics.
650 For example, the Jaccard similarity between text A and B is computed as the number of unique
651 words in the intersection of words from A and B divided by the number of unique words in the
652 union of words from A and B . In a supplementary analysis (Supp. Fig. 5), we compared the
653 LDA-based question-lecture matches we reported in Figure 4 with the Jaccard similarities between
654 each question and each sliding window of text from the corresponding lecture. As shown in
655 Supplementary Figure 5, this simple word-matching approach does not appear to capture the same
656 level of specificity as the LDA-based approach. Whereas the LDA-based approach often yields a
657 clear peak in the time series of correlations between each question and the corresponding lecture,
658 the Jaccard similarity-based approach does not. Furthermore, these LDA-based matches appear
659 to capture conceptual overlaps between the questions and lectures (Supp. Tab. 3), whereas simple
660 word matching does not. For example, one of the example questions examined in Supplementary
661 Figure 5 asks "Which of the following occurs as a cloud of atoms gets more dense?" The LDA-based
662 matches identify lecture timepoints where the relevant *topics* are discussed (e.g., when words like
663 "cloud," "atom," "dense," etc., are mentioned *together*). The Jaccard similarity-based matches,
664 on the other hand, are strong when *any* of these words are mentioned, even if they do not occur
665 together.

666 We view our approach as occupying a sort of "sweet spot," between much larger language
667 models and simple word matching-based approaches, that enables us to capture the relevant

668 conceptual content of course materials at an appropriate semantic scale. Our approach enables us
669 to accurately and consistently identify each question’s content in a way that also matches up with
670 what is presented in the lectures. In turn, this enables us to construct accurate predictions about
671 participants’ knowledge of the conceptual content tested by held-out questions (Fig. 6).

672 One limitation of our approach is that topic models contain no explicit internal representations
673 of more complex aspects of “knowledge,” like knowledge graphs, dependencies or associations
674 between concepts, causality, and so on. These representations might (in principle) be added
675 as extensions to our approach to more accurately and precisely capture, characterize, and track
676 learners’ knowledge. However, modeling these aspects of knowledge will likely require substantial
677 additional research effort.

678 Within the past several years, the global pandemic forced many educators to suddenly adapt to
679 teaching remotely [30, 44, 55, 62]. This change in world circumstances is happening alongside (and
680 perhaps accelerating) geometric growth in the availability of high-quality online courses from plat-
681 forms such as Khan Academy [31], Coursera [63], EdX [33], and others [52]. Continued expansion
682 of the global internet backbone and improvements in computing hardware have also facilitated
683 improvements in video streaming, enabling videos to be easily shared and viewed by increasingly
684 large segments of the world’s population. This exciting time for online course instruction provides
685 an opportunity to re-evaluate how we, as a global community, educate ourselves and each other.
686 For example, we can ask: what defines an effective course or training program? Which aspects of
687 teaching might be optimized and/or augmented by automated tools? How and why do learning
688 needs and goals vary across people? How might we lower barriers to receiving a high-quality
689 education?

690 Alongside these questions, there is a growing desire to extend existing theories beyond the
691 domain of lab testing rooms and into real classrooms [29]. In part, this has led to a recent
692 resurgence of “naturalistic” or “observational” experimental paradigms that attempt to better
693 reflect more ethologically valid phenomena that are more directly relevant to real-world situations
694 and behaviors [45]. In turn, this has brought new challenges in data analysis and interpretation. A
695 key step towards solving these challenges will be to build explicit models of real-world scenarios

696 and how people behave in them (e.g., models of how people learn conceptual content from real-
697 world courses, as in our current study). A second key step will be to understand which sorts
698 of signals derived from behaviors and/or other measurements [e.g., neurophysiological data; 2,
699 16, 42, 46, 49] might help to inform these models. A third major step will be to develop and
700 employ reliable ways of evaluating the complex models and data that are a hallmark of naturalistic
701 paradigms.

702 Beyond specifically predicting what people *know*, the fundamental ideas we develop here also
703 relate to the notion of “theory of mind” of other individuals [22, 27, 41]. Considering others’ unique
704 perspectives, prior experiences, knowledge, goals, etc., can help us to more effectively interact and
705 communicate [50, 54, 57]. One could imagine future extensions of our work (e.g., analogous to
706 the knowledge and learning maps shown in Fig. 8), that attempt to characterize how well-aligned
707 different people’s knowledge bases or backgrounds are. In turn, this might be used to model how
708 knowledge (or other forms of communicable information) flows not just between teachers and
709 students, but between friends having a conversation, individuals on a first date, participants at
710 a business meeting, doctors and patients, experts and non-experts, political allies or adversaries,
711 and more. For example, the extent to which two people’s knowledge maps “match” or “align” in
712 a given region of text embedding space might serve as a predictor of how effectively they will be
713 able to communicate about the corresponding conceptual content.

714 Ultimately, our work suggests a rich new line of questions about the geometric “form” of
715 knowledge, how knowledge changes over time, and how we might map out the full space of
716 what an individual knows. Our finding that detailed estimates about knowledge may be obtained
717 from short quizzes shows one way that traditional approaches to evaluation in education may be
718 extended. We hope that these advances might help pave the way for new approaches to teaching
719 or delivering educational content that are tailored to individual students’ learning needs and goals.

720 **Materials and methods**

721 **Participants**

722 We enrolled a total of 50 Dartmouth undergraduate students in our study. Participants received
723 optional course credit for enrolling. We asked each participant to complete a demographic survey
724 that included questions about their age, gender, native spoken language, ethnicity, race, hearing,
725 color vision, sleep, coffee consumption, level of alertness, and several aspects of their educational
726 background and prior coursework.

727 Participants' ages ranged from 18 to 22 years (mean: 19.52 years; standard deviation: 1.09
728 years). A total of 15 participants reported their gender as male and 35 participants reported their
729 gender as female. A total of 49 participants reported their native language as "English" and 1
730 reported having another native language. A total of 47 participants reported their ethnicity as
731 "Not Hispanic or Latino" and three reported their ethnicity as "Hispanic or Latino." Participants
732 reported their races as White (32 participants), Asian (14 participants), Black or African American
733 (5 participants), American Indian or Alaska Native (1 participant), and Native Hawaiian or Other
734 Pacific Islander (1 participant). (Note that some participants selected multiple racial categories.)

735 A total of 49 participants reporting having normal hearing and 1 participant reported having
736 some hearing impairment. A total of 49 participants reported having normal color vision and 1
737 participant reported being color blind. Participants reported having had, on the night prior to
738 testing, 2–4 hours of sleep (1 participant), 4–6 hours of sleep (9 participants), 6–8 hours of sleep (35
739 participants), or 8+ hours of sleep (5 participants). They reported having consumed, on the same
740 day and leading up to their testing session, 0 cups of coffee (38 participants), 1 cup of coffee (10
741 participants), 3 cups of coffee (1 participant), or 4+ cups of coffee (1 participant).

742 No participants reported that their focus was currently impaired (e.g., by drugs or alcohol).
743 Participants reported their current level of alertness, and we converted their responses to numerical
744 scores as follows: "very sluggish" (-2), "a little sluggish" (-1), "neutral" (0), "fairly alert" (1), and
745 "very alert" (2). Across all participants, a range of alertness levels were reported (range: -2–1;
746 mean: -0.10; standard deviation: 0.84).

747 Participants reported their undergraduate major(s) as “social sciences” (28 participants), “nat-
748 ural sciences” (16 participants), “professional” (e.g., pre-med or pre-law; 8 participants), “mathe-
749 matics and engineering” (7 participants), “humanities” (4 participants), or “undecided” (3 partici-
750 pants). Note that some participants selected multiple categories for their undergraduate major(s).
751 We also asked participants about the courses they had taken. In total, 45 participants reported hav-
752 ing taken at least one Khan Academy course in the past, and 5 reported not having taken any Khan
753 Academy courses. Of those who reported having watched at least one Khan Academy course,
754 7 participants reported having watched 1–2 courses, 11 reported having watched 3–5 courses, 8
755 reported having watched 5–10 courses, and 19 reported having watched 10 or more courses. We
756 also asked participants about the specific courses they had watched, categorized under different
757 subject areas. In the “Mathematics” area, participants reported having watched videos on AP
758 Calculus AB (21 participants), Precalculus (17 participants), Algebra 2 (14 participants), AP Cal-
759 culus BC (12 participants), Trigonometry (11 participants), Algebra 1 (10 participants), Geometry
760 (8 participants), Pre-algebra (7 participants), Multivariable Calculus (5 participants), Differential
761 Equations (5 participants), Statistics and Probability (4 participants), AP Statistics (2 participants),
762 Linear Algebra (2 participants), Early Math (1 participant), Arithmetic (1 participant), and other
763 videos not listed in our survey (5 participants). In the “Science and engineering” area, participants
764 reported having watched videos on Chemistry, AP Chemistry, or Organic Chemistry (21 partic-
765 ipants); Physics, AP Physics I, or AP Physics II (18 participants); Biology, AP Biology; or High
766 school Biology (15 participants); Health and Medicine (1 participant); or other videos not listed
767 in our survey (5 participants). We also asked participants whether they had specifically seen the
768 videos used in our experiment. Of the 45 participants who reported having having taken at least
769 one Khan Academy course in the past, 44 participants reported that they had not watched the *Four*
770 *Fundamental Forces* video, and 1 participant reported that they were not sure whether they had
771 watched it. All participants reported that they had not watched the *Birth of Stars* video. When
772 we asked participants about non-Khan Academy online courses, they reported having watched
773 or taken courses on Mathematics (15 participants), Science and engineering (11 participants), Test
774 preparation (9 participants), Economics and finance (3 participants), Arts and humanities (2 partic-

775 ipants), Computing (2 participants), and other categories not listed in our survey (17 participants).
776 Finally, we asked participants about in-person courses they had taken in different subject areas.
777 They reported taking courses in Mathematics (38 participants), Science and engineering (37 par-
778 ticipants), Arts and humanities (34 participants), Test preparation (27 participants), Economics
779 and finance (26 participants), Computing (14 participants), College and careers (7 participants), or
780 other courses not listed in our survey (6 participants).

781 Experiment

782 We hand-selected two course videos from the Khan Academy platform: *Four Fundamental Forces*
783 (an introduction to gravity, electromagnetism, the weak nuclear force, and the strong nuclear force;
784 duration: 10 minutes and 29 seconds) and *Birth of Stars* (an introduction to how stars are formed;
785 duration: 7 minutes and 57 seconds). All participants viewed the videos in the same order (i.e.,
786 *Four Fundamental Forces* followed by *Birth of Stars*).

787 We then hand-created 39 multiple-choice questions: 15 about the conceptual content of *Four*
788 *Fundamental Forces* (i.e., Lecture 1), 15 about the conceptual content of *Birth of Stars* (i.e., Lecture 2),
789 and 9 questions that tested for general conceptual knowledge about basic physics (covering material
790 that was not presented in either video). To help broaden the set of lecture-specific questions,
791 our team worked through each lecture in small segments to identify what each segment was
792 “about” conceptually, and then write a question about that concept. The general physics questions
793 were drawn our team’s prior coursework and areas of interest, along with internet searches and
794 brainstorming with the project team and other members of J.R.M.’s lab. Although we attempted to
795 design the questions to test “conceptual knowledge,” we note that estimating the specific “amount”
796 of conceptual understanding that each question “requires” to answer is somewhat subjective, and
797 might even come down to the “strategy” a given participant uses to answer the question at that
798 particular moment. The full set of questions and answer choices may be found in Supplementary
799 Table 1. The final set of questions (and response options) was reviewed and approved by J.R.M.
800 before we collected or analyzed the text or experimental data.

801 Over the course of the experiment, participants completed three 13-question multiple-choice

802 quizzes: the first before viewing Lecture 1, the second between Lectures 1 and 2, and the third
803 after viewing Lecture 2 (see Fig. 1). The questions appearing on each quiz, for each participant,
804 were randomly chosen from the full set of 39, with the constraints that (a) each quiz contained
805 exactly 5 questions about Lecture 1, 5 questions about Lecture 2, and 3 questions about general
806 physics knowledge, and (b) each question appear exactly once for each participant. The orders of
807 questions on each quiz, and the orders of answer options for each question, were also randomized.
808 We obtained informed consent from all participants, and our experimental protocol was approved
809 by the Committee for the Protection of Human Subjects at Dartmouth College. We used this
810 experiment to develop and test our computational framework for estimating knowledge and
811 learning.

812 **Analysis**

813 **Statistics**

814 All of the statistical tests performed in our study were two-sided. The 95% confidence intervals
815 we reported for each correlation were estimated by generating 10,000 bootstrap distributions of
816 correlation coefficients by sampling (with replacement) from the observed data.

817 **Constructing text embeddings of multiple lectures and questions**

818 We adapted an approach we developed in prior work [24] to embed each moment of the two
819 lectures and each question in our pool in a common representational space. Briefly, our approach
820 uses a topic model [Latent Dirichlet Allocation; 6] trained on a set of documents, to discover a set
821 of k “topics” or “themes.” Formally, each topic is defined as a distribution of weights over words
822 in the model’s vocabulary (i.e., the union of all unique words, across all documents, excluding
823 “stop words.”). Conceptually, each topic is intended to give larger weights to words that are
824 semantically related (as inferred from their tendency to co-occur in the same document). After
825 fitting a topic model, each document in the training set, or any *new* document that contains at
826 least some of the words in the model’s vocabulary, may be represented as a k -dimensional vector

describing how much the document (most probably) reflects each topic. To select an appropriate k for our model, as a starting point, we identified the minimum number of topics that yielded at least one “unused” topic (i.e., in which all words in the vocabulary were assigned uniform weights) after training. This indicated that the number of topics was sufficient to capture the set of latent themes present in the two lectures (from which we constructed our document corpus, as described below). We found this value to be $k = 15$ topics. We found that with a limited number of additional adjustments following [7], such as removing corpus-specific stop-words, the model yielded (subjectively) sensible and coherent topics. The distribution of weights over words in the vocabulary for each discovered topic is shown in Supplementary Figure 1, and each topic’s top-weighted words may be found in Supplementary Table 2.

As illustrated in Figure 2A, we start by building up a corpus of documents using overlapping sliding windows that span each video’s transcript. Khan Academy provides professionally created, manual transcriptions of all videos for closed captioning. However, such transcripts would not be readily available in all contexts to which our framework could potentially be applied. Khan Academy videos are hosted on the YouTube platform, which additionally provides automated captions. We opted to use these automated transcripts [which, in prior work, we have found to be of sufficiently near-human quality to yield reliable data in behavioral studies; 64] when developing our framework in order to make it more directly extensible and adaptable by others in the future.

We fetched these automated transcripts using the `youtube-transcript-api` Python package [14]. The transcripts consisted of one timestamped line of text for every few seconds (mean: 2.34 s; standard deviation: 0.83 s) of spoken content in the video (i.e., corresponding to each individual caption that would appear on-screen if viewing the lecture via YouTube, and when those lines would appear). We defined a sliding window length of (up to) $w = 30$ transcript lines, and assigned each window a timestamp corresponding to the midpoint between the timestamps for its first and last lines. This w parameter was chosen to match the same number of words per sliding window (rounded to the nearest whole word, and before preprocessing) as the sliding windows we defined in our prior work [24] (i.e., 185 words per sliding window).

These sliding windows ramped up and down in length at the beginning and end of each

855 transcript, respectively. In other words, each transcript’s first sliding window covered only its first
856 line, the second sliding window covered the first two lines, and so on. This ensured that each line
857 from the transcripts appeared in the same number (w) of sliding windows. We next performed a
858 series of standard text preprocessing steps: normalizing case, lemmatizing, removing punctuation
859 and removing stop-words. We constructed our corpus of stop words by augmenting the Natural
860 Language Toolkit [NLTK; 3] English stop word list with the following additional words, selected
861 using one of the approaches suggested by [7]: “actual,” “actually,” “also,” “bit,” “could,” “e,”
862 “even,” “first,” “follow,” “following,” “four,” “let,” “like,” “mc,” “really,” “saw,” “see,” “seen,”
863 “thing,” and “two.” This yielded sliding windows with an average of 73.8 remaining words, and
864 lasting for an average of 62.22 seconds. We treated the text from each sliding window as a single
865 “document,” and combined these documents across the two videos’ windows to create a single
866 training corpus for the topic model.

867 After fitting a topic model to the two videos’ transcripts, we could use the trained model to
868 transform arbitrary (potentially new) documents into k -dimensional topic vectors. A convenient
869 property of these topic vectors is that documents that reflect similar blends of topics (i.e., documents
870 that reflect similar themes, according to the model) will yield similar coordinates (in terms of
871 correlation, cosine similarity, Kullback-Leibler divergence, Euclidean distance, or other geometric
872 measures). In general, the similarity between different documents’ topic vectors may be used to
873 characterize the similarity in conceptual content between the documents.

874 We transformed each sliding window’s text into a topic vector, and then used linear interpolation
875 (independently for each topic dimension) to resample the resulting time series to one vector
876 per second. We also used the fitted model to obtain topic vectors for each question in our pool (see
877 Supp. Tab. 1). Taken together, we obtained a *trajectory* for each video, describing its path through
878 topic space, and a single coordinate for each question (Fig. 2C). Embedding both videos and all of
879 the questions using a common model enables us to compare the content from different moments
880 of videos, compare the content across videos, and estimate potential associations between specific
881 questions and specific moments of video.

882 **Estimating dynamic knowledge traces**

883 We used the following equation to estimate each participant's knowledge about timepoint t of a
884 given lecture, $\hat{k}(t)$:

$$\hat{k}(f(t, L)) = \frac{\sum_{i \in \text{correct}} \text{ncorr}(f(t, L), f(i, Q))}{\sum_{j=1}^N \text{ncorr}(f(t, L), f(j, Q))}, \quad (1)$$

885 where

$$\text{ncorr}(x, y) = \frac{\text{corr}(x, y) - \text{mincorr}}{\text{maxcorr} - \text{mincorr}}, \quad (2)$$

886 and where mincorr and maxcorr are the minimum and maximum correlations between any lecture
887 timepoint and question, taken over all timepoints in the given lecture, and all five questions *about*
888 that lecture appearing on the given quiz. We also define $f(s, \Omega)$ as the s^{th} topic vector from the set
889 of topic vectors Ω . Here t indexes the set of lecture topic vectors, L , and i and j index the topic
890 vectors of questions used to estimate the knowledge trace, Q . Note that "correct" denotes the set
891 of indices of the questions the participant answered correctly on the given quiz.

892 Intuitively, $\text{ncorr}(x, y)$ is the correlation between two topic vectors (e.g., the topic vector from one
893 timepoint in a lecture, x , and the topic vector for one question, y), normalized by the minimum and
894 maximum correlations (across all timepoints t and questions Q) to range between 0 and 1, inclusive.
895 Equation 1 then computes the weighted average proportion of correctly answered questions about
896 the content presented at timepoint t , where the weights are given by the normalized correlations
897 between timepoint t 's topic vector and the topic vectors for each question. The normalization step
898 (i.e., using ncorr instead of the raw correlations) ensures that every question contributes some
899 non-negative amount to the knowledge estimate.

900 **GLMM METHODS SECTION PLACEHOLDER**

901 **Estimating the "smoothness" of knowledge**

902 In the analysis reported in Figure 7A, we show how participants' ability to correctly answer
903 quiz questions changes as a function of distance from a given correctly or incorrectly answered

904 reference question. We used a bootstrap-based approach to estimate the maximum distances over
905 which these proportions of correctly answered questions could be reliably distinguished from
906 participants' overall average proportion of correctly answered questions.

907 For each of 10,000 iterations, we drew a random subsample (with replacement) of 50 participants
908 from our dataset **full dataset**. Within each iteration, we first computed the 95% confidence interval
909 (CI) of the across-subsample-participants mean proportion correct on each of the three quizzes,
910 separately. To compute this interval for each quiz, we repeatedly (1,000 times) subsampled par-
911 ticipants (with replacement, from the outer subsample for the current iteration) and computed
912 the mean proportion correct *of* each of these inner subsamples. We then identified the 2.5th and
913 97.5th percentiles of the resulting distributions of 1,000 means. These three intervals (one for each
914 quiz) served as our thresholds for confidence that the proportion correct within a given distance
915 from a reference question was reliably different (at the $p < 0.05$ significance level) from the average
916 proportion correct across all questions on the given quiz.

917 Next, for each participant in the current subsample, and for each of the three quizzes they
918 completed (separately), we iteratively treated each of the 15 questions appearing on the given
919 quiz as the “reference” question. We constructed a series of concentric 15-dimensional “spheres”
920 centered on the reference question’s embedding space coordinate, where each successive sphere’s
921 radius increased by 0.01 (correlation distance) between 0 and 2, inclusive (i.e., tiling the range
922 of possible correlation distances with 201 spheres in total). We then computed the proportion
923 of questions enclosed within each sphere that the participant answered correctly, and averaged
924 these per-radius proportion correct scores across reference questions that were answered correctly,
925 and those that were answered incorrectly. This resulted in two number-of-spheres sequences of
926 proportion-correct scores for each subsample participant and quiz: one derived from correctly
927 answered reference questions, and one derived from incorrectly answered reference questions.

928 We computed the across-subsample-participants mean proportion correct for each radius value
929 (i.e., sphere) and “correctness” of reference question. This yielded two sequences of proportion-
930 correct scores for each quiz, analogous to the blue and red lines displayed in Figure 7A, but for
931 the present subsample. For each quiz, we then found the minimum distance from the reference

932 question (i.e., sphere radius) at which each of these two sequences of per-radius proportion correct
933 scores intersected the 95% confidence interval for the overall proportion correct (i.e., analogous to
934 the black error bands in Fig. 7A).

935 This resulted in two “intersection” distances for each quiz (for correctly answered and incor-
936 rectly answered reference questions). Repeating this full process for each of the 10,000 bootstrap
937 iterations output two distributions of intersection distances for each of the three quizzes. The
938 means and 95% confidence intervals for these distributions are plotted in Figure 7B.

939 **Creating knowledge and learning map visualizations**

940 An important feature of our approach is that, given a trained text embedding model and partic-
941 ipants’ quiz performance on each question, we can estimate their knowledge about *any* content
942 expressible by the embedding model—not solely the content explicitly probed by the quiz ques-
943 tions, or even appearing in the lectures. To visualize these estimates (Fig. 8, Supp. Figs. 7, 8, 9, 10,
944 and 11), we used Uniform Manifold Approximation and Projection [UMAP; 39, 40] to construct a
945 2D projection of the text embedding space. Whereas our main analyses used a 15-topic embedding
946 space, we used a 100-topic embedding space for these visualizations. This change in the number
947 of topics overcame an undesirable behavior in the UMAP embedding procedure, whereby embed-
948 ding coordinates for the 15-topic model tended to be “clumped” into separated clusters, rather
949 than forming a smooth trajectory through the 2D space. When we increased the number of topics
950 to 100, the embedding coordinates in the 2D space formed a smooth trajectory through the space,
951 with substantially less clumping (Fig. 8). Creating a “map” by sampling this 100-dimensional
952 space at high resolution to obtain an adequate set of topic vectors spanning the embedding space
953 would be computationally intractable. However, sampling a 2D grid is trivial.

954 At a high level, the UMAP algorithm obtains low-dimensional embeddings by minimizing
955 the cross-entropy between the pairwise (clustered) distances between the observations in their
956 original (e.g., 100-dimensional) space and the pairwise (clustered) distances in the low-dimensional
957 embedding space (in our approach, the embedding space is 2D). In our implementation, pairwise
958 distances in the original high-dimensional space were defined as 1 minus the correlation between

959 each pair of coordinates, and pairwise distances in the low-dimensional embedding space were
960 defined as the Euclidean distance between each pair of coordinates.

961 In our application, all of the coordinates we embedded were topic vectors, whose elements
962 are always non-negative and sum to one. Although UMAP is an invertible transformation at
963 the embedding locations of the original data, other locations in the embedding space will not
964 necessarily follow the same implicit “rules” as the original high-dimensional data. For example,
965 inverting an arbitrary coordinate in the embedding space might result in negative-valued vectors,
966 which are incompatible with the topic modeling framework. To protect against this issue, we
967 log-transformed the topic vectors prior to embedding them in the 2D space. When we inverted
968 the embedded vectors (e.g., to estimate topic vectors or word clouds, as in Fig. 8C), we passed
969 the inverted (log-transformed) values through the exponential function to obtain a vector of non-
970 negative values, and normalized them to sum to one.

971 After embedding both lectures’ topic trajectories and the topic vectors of every question, we
972 defined a rectangle enclosing the 2D projections of the lectures’ and quizzes’ embeddings. We then
973 sampled points from a regular 100×100 grid of coordinates that evenly tiled this enclosing rectangle.
974 We sought to estimate participants’ knowledge (and learning, i.e., changes in knowledge) at each
975 of the resulting 10,000 coordinates.

976 To generate our estimates, we placed a set of 39 radial basis functions (RBFs) throughout the
977 embedding space, centered on the 2D projections for each question (i.e., we included one RBF for
978 each question). At coordinate x , the value of an RBF centered on a question’s coordinate μ , is given
979 by:

$$\text{RBF}(x, \mu, \lambda) = \exp \left\{ -\frac{\|x - \mu\|^2}{\lambda} \right\}. \quad (3)$$

980 The λ term in the RBF equation controls the “smoothness” of the function, where larger values
981 of λ result in smoother maps. In our implementation we used $\lambda = 50$. Next, we estimated the
982 “knowledge” at each coordinate, x , using:

$$\hat{k}(x) = \frac{\sum_{i \in \text{correct}} \text{RBF}(x, q_i, \lambda)}{\sum_{j=1}^N \text{RBF}(x, q_j, \lambda)}. \quad (4)$$

983 Intuitively, Equation 4 computes the weighted proportion of correctly answered questions, where
984 the weights are given by how nearby (in the 2D space) each question is to the x . We also defined
985 *learning maps* as the coordinate-by-coordinate differences between any pair of knowledge maps.
986 Intuitively, learning maps reflect the *change* in knowledge across two maps.

987 **Author contributions**

988 Conceptualization: P.C.F., A.C.H., and J.R.M. Methodology: P.C.F., A.C.H., and J.R.M. Software:
989 P.C.F. Validation: P.C.F. Formal analysis: P.C.F. Resources: P.C.F., A.C.H., and J.R.M. Data curation:
990 P.C.F. Writing (original draft): J.R.M. Writing (review and editing): P.C.F., A.C.H., and J.R.M. Visu-
991 alization: P.C.F. and J.R.M. Supervision: J.R.M. Project administration: P.C.F. Funding acquisition:
992 J.R.M.

993 **Data availability**

994 All of the data analyzed in this manuscript may be found at <https://github.com/ContextLab/efficient-learning-khan>.
995

996 **Code availability**

997 All of the code for running our experiment and carrying out the analyses may be found at
998 <https://github.com/ContextLab/efficient-learning-khan>.

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