

1 **Geometric models reveal the hidden structure of**
2 **conceptual knowledge**

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4 **Abstract**

5 We develop a mathematical framework, based on natural language processing models, for
6 tracking and characterizing the acquisition of conceptual knowledge. Our approach embeds each
7 concept in a high dimensional representation space, where nearby coordinates reflect similar or
8 related concepts. We tested our approach using behavioral data collected from a group of
9 college students. In the experiment, we asked the participants to answer sets of quiz questions
10 interleaved between watching two course videos from the Khan Academy platform. We applied
11 our framework to the videos' transcripts, and to text of the quiz questions, to quantify the
12 content of each moment of video and each quiz question. We used these embeddings, along with
13 participants' quiz responses, to track how the learners' knowledge changed after watching each
14 video. Our findings show how a limited set of quiz questions may be used to construct rich and
15 meaningful representations of what each learner knows, and how their knowledge changes over
16 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 “map” of everything a student knew. Defining
²⁰ what such a map might even look like, let alone how it might be constructed or filled in, is itself
²¹ a non-trivial problem. But if a teacher *were* to gain access to such a map, how might that change
²² their ability to teach the student? Perhaps they might start by checking how well the student knew
²³ the to-be-learned information already, or how much they knew about related concepts. For some
²⁴ students, they could potentially optimize their teaching efforts to maximize efficiency by focusing
²⁵ primarily on not-yet-known content. For other students (or other content areas), it might be more
²⁶ effective to optimize for direct connections between already-known content and any new material.
²⁷ Observing how the student’s knowledge was changing over time, in response to their training,
²⁸ could also help to guide the teacher.

²⁹ Designing and building procedures and tools for mapping out knowledge touches on deep
³⁰ questions about what it means to learn. For example, how do we acquire conceptual knowledge?
³¹ Memorizing course lectures or textbook chapters by rote can lead to the superficial *appearance*
³² of understanding the underlying content, but achieving true conceptual understanding seems to
³³ require something deeper and richer. Does conceptual understanding entail connecting newly
³⁴ acquired information to the scaffolding of one’s existing knowledge or experience [1, 5, 7, 8, 22]?
³⁵ Or weaving a lecture’s atomic elements (e.g., its component words) into a structured network
³⁶ that describes how those individual elements are related? Conceptual understanding could also
³⁷ involve building a mental model that transcends the meanings of those individual atomic elements
³⁸ by reflecting the deeper meaning underlying the gestalt whole [14, 16, 21].

³⁹ The difference between “understanding” and “memorizing,” as framed by the researchers
⁴⁰ in education, cognitive psychology, and cognitive neuroscience [9, 10, 13, 16, 21] has profound
⁴¹ analogs in the fields of natural language processing and natural language understanding. For
⁴² example, considering the raw contents of a document (e.g., its constituent symbols, letters, and
⁴³ words) might provide some information about what the document is about, just as memorizing
⁴⁴ a passage might be used to answer simple questions about the passage [e.g., whether it might

45 contain words related to furniture versus physics; 2, 3, 15]. However, modern natural language
46 processing models [e.g., 4, 6, 20] also attempt to capture the deeper meaning *underlying* those
47 atomic elements. These models consider not only the co-occurrences of those elements within
48 and across documents, but also patterns in how those elements appear across different scales (e.g.,
49 sentences, paragraphs, chapters, etc.), the temporal and grammatical properties of the elements,
50 and other high-level characteristics of how they are used [17, 18]. According to these models, the
51 deep conceptual meaning of a document may be captured by a feature vector in a high-dimensional
52 representation space, where nearby vectors reflect conceptually related documents. A model that
53 succeeds at capturing an analog of “understanding” is able to assign nearby feature vectors to
54 two conceptually related documents, *even when the words contained in those documents have very little*
55 *overlap.*

56 Given these insights, what form might the representation of the sum total of a person’s knowl-
57 edge take? First, we might require a means of systematically describing or representing the nearly
58 infinite set of possible things a person could know. Second, we might want to account for potential
59 associations between different concepts. For example, the concepts of “fish” and “water” might be
60 associated in the sense that fish live in water. Third, knowledge may have a critical dependency
61 structure, such that knowing about a particular concept might require first knowing about a set of
62 other concepts. For example, understanding the concept of a fish swimming in water first requires
63 understanding what fish and water *are*. Fourth, as we learn, our “current state of knowledge”
64 should change accordingly. Learning new concepts should both update our characterizations of
65 “what is known” and should also unlock any now-satisfied dependencies of that newly learned
66 concept so that they are “tagged” as available for future learning.

67 Here we develop a framework for modelling how knowledge is acquired during learning. The
68 central idea is to use text embedding models to define the coordinate systems of two maps: (a) a
69 *knowledge map* that describes the extent to which each concept is currently known and (b) a *learning*
70 *map* that describes the extent to which each concept could be learned. Each location on these maps
71 represents a single concept, and the geometries are defined such that related concepts are located
72 nearby in space. We use this framework to analyze and interpret behavioral data collected from an

73 experiment that has participants watch and answer conceptual questions about a series of recorded
74 course lectures.

75 Our primary research goal is to advance our understanding of what it means to acquire deep
76 real-world conceptual knowledge. Traditional laboratory approaches to studying learning and
77 memory (e.g., list learning studies) often draw little distinction between memorization and under-
78 standing. Instead, these studies typically focus on whether information is effectively encoded or
79 retrieved, rather than whether the information is *understood*. Approaches to studying conceptual
80 learning, such as category learning experiments, can start to investigate the distinction between
81 memorization and understanding, often by training participants to distinguish arbitrary or ran-
82 dom features in otherwise meaningless categorized stimuli. However the objective of real-world
83 training, or learning from life experiences more generally, is often to develop new knowledge that
84 may be applied in *useful* ways in the future. In this sense, the gap between modern learning theo-
85 ries and modern pedagogical approaches and classroom learning strategies is enormous: most of
86 our theories about *how* people learn are inspired by experimental paradigms and models that have
87 only peripheral relevance to the kinds of learning that students and teachers actually seek. To help
88 bridge this gap, our study uses course materials from real online courses to inform, fit, and test
89 models of real-world conceptual learning. We also provide a “proof of concept” demonstration
90 of how our models might be used to construct “maps” of what students know, and how their
91 knowledge changes with training. In addition to helping to visualize knowledge (and changes
92 in knowledge), we hope that such maps might lead to real-world tools for improving how we
93 educate.

94 Results

95 At its core, our main modeling approach is based around a simple assumption that we sought to test
96 empirically: all else being equal, knowledge about a given concept is predictive of knowledge about
97 similar or related concepts. From a geometric perspective, this assumption implies that knowledge
98 is fundamentally “smooth.” In other words, as one moves through a space representing someone’s

99 knowledge (where similar concepts occupy nearby coordinates), their “level of knowledge” should
100 change relatively gradually throughout that space. To begin to test this smoothness assumption,
101 we sought to track our participants’ knowledge and how it changed over time in response to
102 training.

103 We asked our participants to answer questions from several multiple choice quizzes and watch
104 two lecture videos from the *Khan Academy* platform (Fig. 1). One lecture video, entitled *Four*
105 *Fundamental Forces*, was about the four fundamental forces in physics: gravity, strong and weak
106 interactions, and electromagnetism. The second lecture video, entitled *Birth of Stars*, provides
107 an overview of our current understanding of how stars form. We selected both lessons to be (a)
108 accessible to a broad audience, e.g., by minimizing prerequisite knowledge, (b) largely independent
109 of each other, e.g., so that the two videos focused on different material and did not depend on
110 each other, and (c) related to each other, e.g., so that both videos contained at least *some* similar
111 or overlapping content. The two videos we selected are introductory, about different primary
112 concepts, but also touch on “physics” and “astronomy” themes. We also wrote a set of multiple
113 choice quiz questions that would enable us to test participants’ knoweldge about each individual
114 video and about related content not specifically presented in either video (Tab. S1). Participants
115 answered questions randomly drawn from each content area (lecture 1, lecture 2, and general
116 physics knowledge) across each of three quizzes. Quiz 1 was intended to assessed participants’
117 knowledge before training; quiz 2 assessed knowledge after watching the Four Fundamental Forces
118 video (i.e., lecture 1); and quiz 3 assessed knowledge after watching the Birth of Stars video (i.e.,
119 lecture 2).

120 We trained a text embedding model using sliding windows of text from the two videos’ trans-
121 scripts (see *Constructing text embeddings of multiple videos and questions*). We also used the same
122 model (i.e., trained on the videos’ transcripts) to embed the text of each question in our pool. This
123 yielded, for each second of each video, and for each question, a single topic vector—i.e., a coordinate
124 in a text embedding space (Fig. 6). Intuitively, each dimension of the embedding space corresponds
125 to a “theme” or “topic” reflected in some part(s) of the videos (Tab. S2), and the coordinates in
126 embedding space denote the blend of themes reflected by a particular excerpt of text (e.g., from

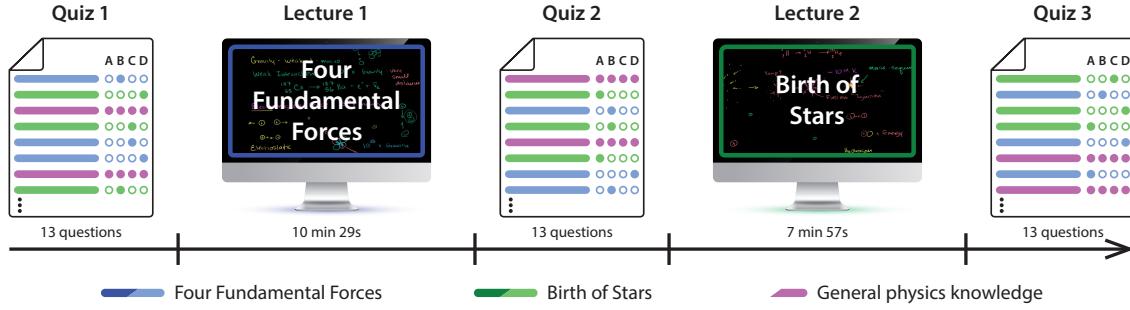


Figure 1: Experimental paradigm. Participants alternate between answering 13-question multiple choice quizzes and watching two Khan academy videos. Each quiz contains a mix of 5 questions about lecture 1, 5 questions about lecture 2, and 3 general physics knowledge questions. The specific questions reflected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

¹²⁷ part of a video’s transcript, from a question, etc.).

¹²⁸ Although a single lecture may be organized a single broad theme at a coarse scale, at a finer
¹²⁹ scale each moment of a lecture typically covers a narrower range of content. We wondered whether
¹³⁰ a text embedding model trained on the lectures’ transcripts might capture some of this finer scale
¹³¹ content. For example, if a particular question asks about the content from one small part of a
¹³² lecture, we wondered whether our text embedding model could be used to automatically identify
¹³³ the “matching” moment(s) in the lecture. When we correlated each question’s topic vector with
¹³⁴ the topic vectors for each second of the lectures, we found some evidence that each question is
¹³⁵ temporally specific (Fig. 2). In particular, most questions’ topic vectors were maximally correlated
¹³⁶ with a well-defined range of timepoints from their corresponding lectures, and the correlations fell
¹³⁷ off sharply outside of that range. We also examined the best-matching intervals for each question
¹³⁸ qualitatively by comparing the text of the question to the text of the most-correlated parts of the
¹³⁹ lectures. Despite that the questions were excluded from the text embedding model’s training set,
¹⁴⁰ in general we found a close correspondence between the conceptual content that each question
¹⁴¹ covered and the content covered by the best-matching moments of the lectures. Two representative
¹⁴² examples are shown at the bottom of Fig. 2.

¹⁴³ The ability to quantify how much each question is “asking about” each moment of the lectures
¹⁴⁴ could enable high-resolution insights into participants’ knowledge. Traditional approaches to

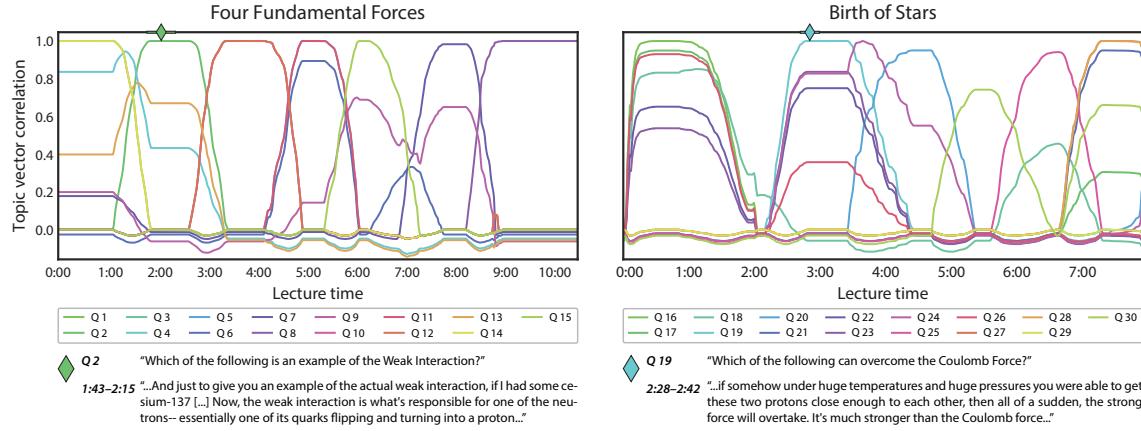


Figure 2: Which parts of each lecture are captured by each question? Each panel displays timeseries plots showing how each question’s topic vector correlates with each video timepoint’s topic vector. The left panel displays these correlations for the *Four Fundamental Forces* lecture and associated questions, and the right panels displays these 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 questions, in the indicated lectures. The associated questions’ text, and snippets of the lectures’ transcripts in the best-matching sliding windows, are displayed at the bottom of the figure.

145 estimating how much a student “knows” about the content of a given lecture entail computing
 146 the proportion of correctly answered questions. But if two students receive identical scores on an
 147 exam, might our modeling framework help us to gain more nuanced insights into the *specific* content
 148 that each student has mastered (or failed to master)? For example, a student who misses three
 149 questions that were all about the same concept (e.g., concept *A*) will have gotten the same *proportion*
 150 of questions correct as another student who missed three questions about three *different* concepts
 151 (e.g., *A*, *B*, and *C*). But if we wanted to fill in the “gaps” in the two students’ understandings,
 152 we might do well to focus on concept *A* for the first student, but add in concepts *B* and *C* for the
 153 second student.

154 **JRM STOPPED HERE...**

155 As a sanity check, we anticipated that our knowledge estimates should show a content-specific
 156 “boost” in participants’ knowledge after watching each video.

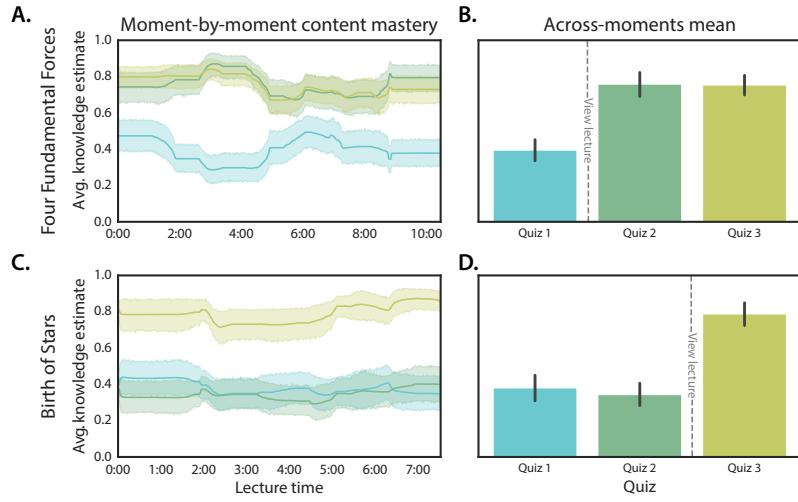


Figure 3: Estimating moment-by-moment knowledge acquisition. **A. Moment-by-moment knowledge about the *Four Fundamental Forces*.** Each trace displays the weighted proportion of correctly answered questions about the content reflected in each moment of the lecture (see *Estimating dynamic knowledge traces*), using responses from one quiz (color). The traces are averaged across participants. **B. Average estimated knowledge about the *Four Fundamental Forces*.** Each bar displays the across-timepoint average knowledge, estimated using the responses to one quiz's questions. **C. Moment-by-moment knowledge about the *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 the *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.

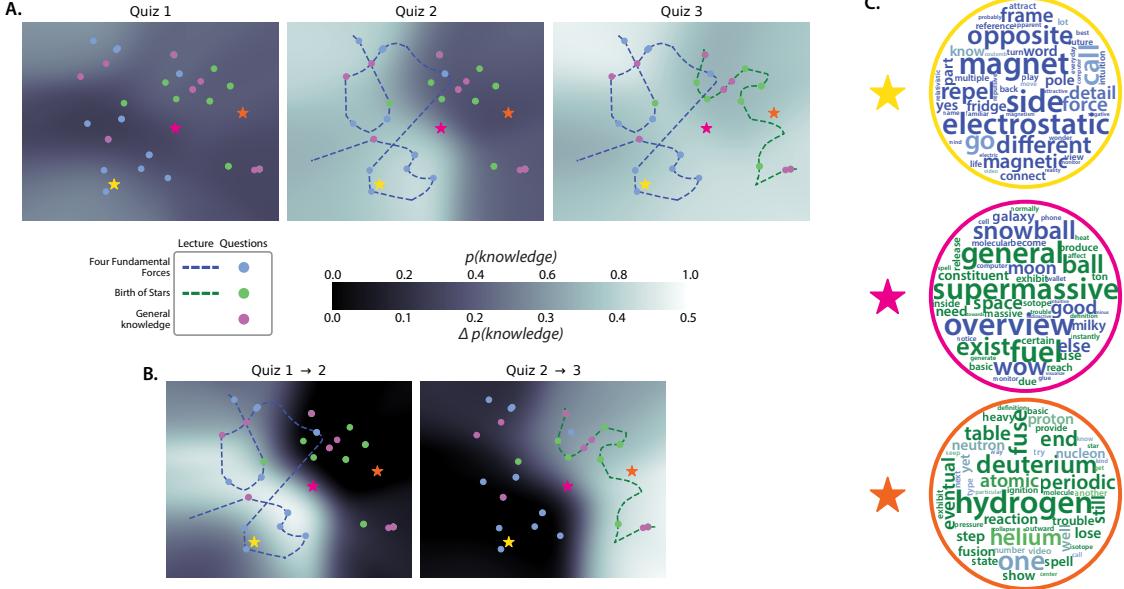


Figure 4: Mapping out the geometry of knowledge and learning. **A. Average “knowledge maps” estimated using each quiz.** Each map displays a 2D projection of the estimated knowledge about the content reflected by all regions of topic space (see *Creating knowledge and learning map visualizations*). The topic trajectories of each lecture and the coordinates of each question are indicated by dotted lines and dots. Each map reflects an average across all participants. For individual participants’ maps, see Figures S1, S2, and S3. **B. Average “learning maps” estimated between each successive pair of quizzes.** The learning maps are in the same general format as the knowledge maps in Panel A, but each coordinate in the learning maps indicates the difference between the corresponding coordinates in the indicated pair of knowledge maps—i.e., how much the estimated knowledge “changed” across the two quizzes. Each map reflects an average across all participants. For individual participants’ maps, see Figures S4 and S5. **C. Word clouds for sampled points in topic space.** Each word cloud displays the relative weights of each word reflected by the blend of topics represented at the locations of the stars in the maps. The words’ colors indicate how much each word is weighted on average across all timepoints’ topic vectors in the *Four Fundamental Forces* (blue) and *Birth of Stars* (green) videos, respectively.

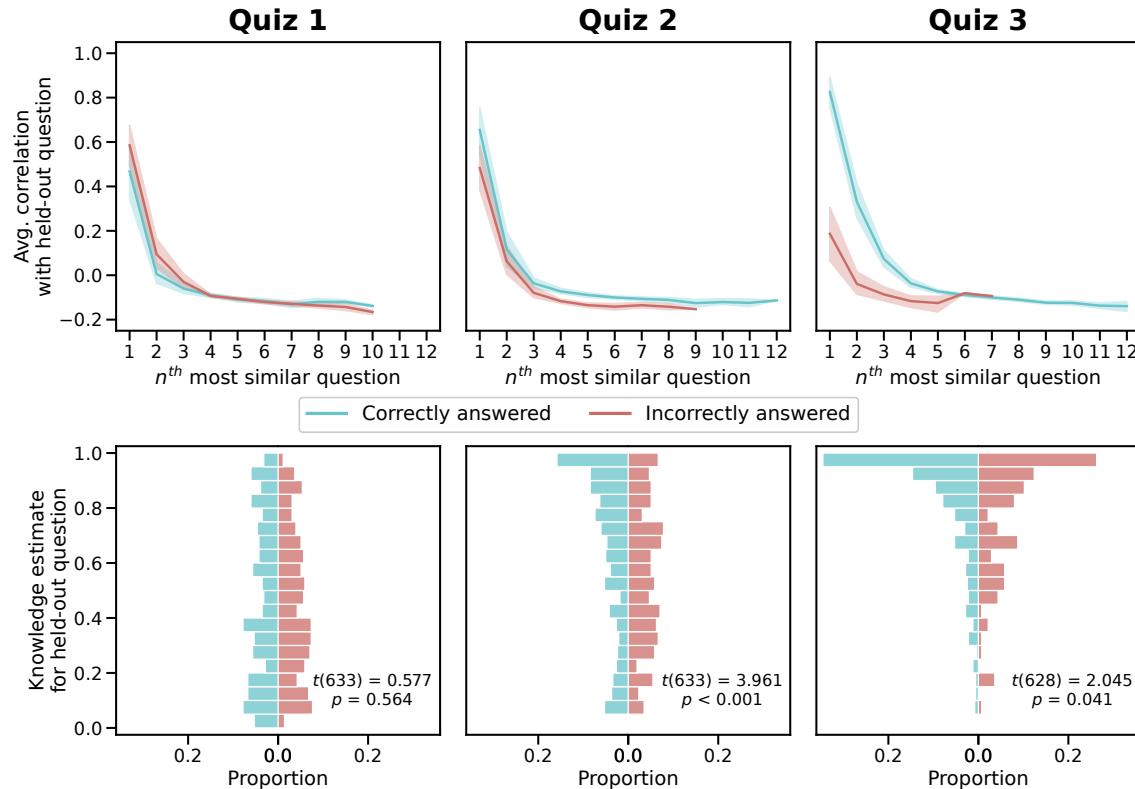


Figure 5: Estimating knowledge for held-out questions.

¹⁵⁷ **Discussion**

¹⁵⁸ **Materials and methods**

¹⁵⁹ **Participants**

¹⁶⁰ We enrolled a total of 50 Dartmouth undergraduate students in our study. Participants received
¹⁶¹ course credit for enrolling. We asked each participant to fill out a demographic survey that included
¹⁶² questions about their age, gender, native spoken language, ethnicity, race, hearing, color vision,
¹⁶³ sleep, coffee consumption, level of alertness, and several aspects of their educational background
¹⁶⁴ and prior coursework.

¹⁶⁵ Participants' ages ranged from 18 to 22 years (mean: 19.52 years; standard deviation: 1.09
¹⁶⁶ years). A total of 15 participants reported their gender as male and 35 participants reported their
¹⁶⁷ gender as female. A total of 49 participants reported their native language as "English" and 1
¹⁶⁸ reported having another native language. A total of 47 participants reported their ethnicity as
¹⁶⁹ "Not Hispanic or Latino" and three reported their ethnicity as "Hispanic or Latino." Participants
¹⁷⁰ reported their races as White (32 participants), Asian (14 participants), Black or African American
¹⁷¹ (5 participants), American Indian or Alaska Native (1 participant), and Native Hawaiian or Other
¹⁷² Pacific Islander (1 participant). (Note that some participants selected multiple racial categories.)

¹⁷³ A total of 49 participants reporting having normal hearing and 1 participant reported having
¹⁷⁴ some hearing impairment. A total of 49 participants reported having normal color vision and 1
¹⁷⁵ participant reported being color blind. Participants reported having had, on the night prior to
¹⁷⁶ testing, 2 – 4 hours of sleep (1 participant), 4 – 6 hours of sleep (9 participants), 6 – 8 hours of sleep
¹⁷⁷ (35 participants), or 8+ hours of sleep (5 participants). They reported having consumed, on the
¹⁷⁸ same day and leading up to their testing session, 0 cups of coffee (38 participants), 1 cup of coffee
¹⁷⁹ (10 participants), 3 cups of coffee (1 participant), or 4+ cups of coffee (1 participant).

¹⁸⁰ No participants reported that their focus was currently impaired (e.g., by drugs or alcohol).
¹⁸¹ Participants reported their current level of alertness, and we converted their responses to numerical
¹⁸² scores as follows: "very sluggish" (-2), "a little sluggish" (-1), "neutral" (0), "fairly alert" (1), and

¹⁸³ “very alert” (2). Across all participants, a range of alertness levels were reported (range: -2 – 1;
¹⁸⁴ mean: -0.10; standard deviation: 0.84).

¹⁸⁵ Participants reported their undergraduate major(s) as Social Sciences (28 participants), Natural
¹⁸⁶ sciences (16), Professional (e.g., pre-med or pre-law; 8 participants), Mathematics and engineering
¹⁸⁷ (7 participants), Humanities (4 participants), or Undecided (3 participants). Note that some par-
¹⁸⁸ ticipants selected multiple categories for their undergraduate major. We also asked participants
¹⁸⁹ about the courses they had taken. In total, 46 participants reported having taken at least one Khan
¹⁹⁰ academy course in the past or being familiar with the Khan academy, and 4 reported not having
¹⁹¹ taken any Khan academy courses. Of the participants who reported having watched at least one
¹⁹² Khan academy course, 1 participant declined to report the number of courses they had watched;
¹⁹³ 7 participants reported having watched 1–2 courses; 11 reported having watched 3–5 courses; 8
¹⁹⁴ reported having watched 5–10 courses; and 19 reported having watched 10 or more courses. We
¹⁹⁵ also asked participants about the specific courses they had watched, categorized under different
¹⁹⁶ subject areas. In the “Mathematics” area participants reported having watched videos on AP
¹⁹⁷ Calculus AB (21 participants), Precalculus (17 participants), Algebra 2 (14 participants), AP Cal-
¹⁹⁸ culus BC (12 participants), Trigonometry (11 participants), Algebra 1 (10 participants), Geometry
¹⁹⁹ (8 participants), Pre-algebra (7 participants), Multivariable Calculus (5 participants), Differential
²⁰⁰ Equations (5 participants), Statistics and Probability (4 participants), AP Statistics (2 participants),
²⁰¹ Linear Algebra (2 participants), Early Math (1 participant), Arithmetic (1 participant), and other
²⁰² videos not listed in our survey (6 participants). In the “Science and engineering” area participants
²⁰³ reported having watched videos on Chemistry, AP Chemistry, or Organic Chemistry (21 partic-
²⁰⁴ ipants); Physics, AP Physics I, or AP Physics II (15 participants); Biology, AP Biology; or High
²⁰⁵ school Biology (15 participants); Health and Medicine (1 participant); or other videos not listed in
²⁰⁶ our survey (20 participants). We also asked participants if they had specifically seen the videos
²⁰⁷ used in our experiment. When we asked about the *Four Fundamental Forces* video, 45 participants
²⁰⁸ reported not having watched it before, 1 participant reported that they were not sure if they had
²⁰⁹ watched it before, and 4 participants declined to respond. When we asked about the *Birth of*
²¹⁰ *Stars* video, 46 participants reported not having watched it before and 4 participants declined to

211 respond. When we asked participants about non-Khan academy online courses, they reported
212 having watched or taken courses on Mathematics (15 participants), Science and engineering (11
213 participants), Test preparation (9 participants), Economics and finance (3 participants), Arts and
214 humanities (2 participants), Computing (2 participants), and other categories not listed in our
215 survey (18 participants). Finally, we asked participants about in-person courses they had taken in
216 different subject areas. They reported taking courses in Mathematics (39 participants), Science and
217 engineering (38 participants), Arts and humanities (35 participants), Test preparation (27 participants),
218 Economics and finance (26 participants), Computing (15 participants), College and careers
219 (7 participants), or other courses not listed in our survey (6 participants).

220 **Experiment**

221 We hand-selected two roughly 10-minute course videos from the Khan Academy platform: *The*
222 *Four Fundamental Forces* (an introduction to gravity, electromagnetism, the weak nuclear force, and
223 the strong nuclear force; duration: 10 minutes and 29 seconds) and *Birth of Stars* (an introduction
224 to how stars are formed; duration: 7 minutes and 57 seconds). We hand-wrote 39 multiple
225 choice questions: 15 about the conceptual content of *The Four Fundamental Forces*, another 15 about
226 the conceptual content of *Birth of Stars*, and 9 other questions that tested for general conceptual
227 knowledge about basic physics (covering material that was not presented in either video). The full
228 set of questions may be found in Table S1.

229 Participants began the main experiment by answering a battery of 13 randomly selected ques-
230 tions (chosen from the full set of 39). Then they watched the *The Four Fundamental Forces* video.
231 Next, they answered a second set of 13 questions (chosen at random from the remaining 26 ques-
232 tions). Fourth, participants watch the *Birth of Stars* video, and finally they answered the remaining
233 13 questions. Our experimental procedure is diagramed in Figure 1. We used the experiment to
234 develop and test our computational framework for estimating knowledge and learning maps.

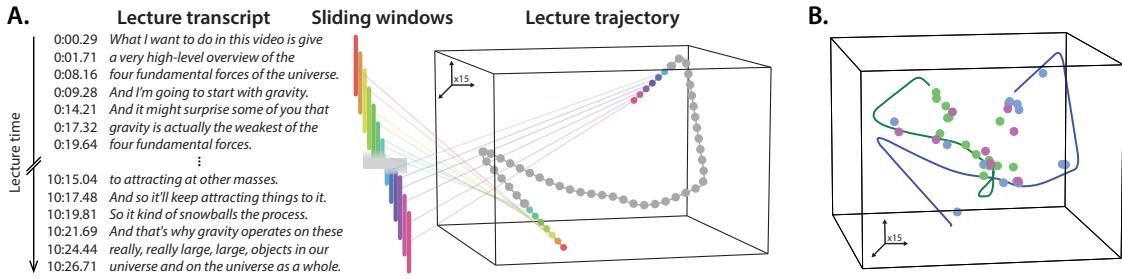


Figure 6: Constructing video content *trajectories*. **A.** Building a document pool from sliding windows of text. We decompose each video’s transcript into a series of overlapping sliding windows. The set of transcript snippets (across all windows) may be treated as a set of “documents” for training a text embedding model. After training a text embedding model using the two videos’ sliding windows, along with the text from each question in our pool (Tab. S1), we construct “trajectories” through text embedding space by joining the embedding coordinates of successive sliding windows from each video. **B. Embedding multiple videos and questions.** Applying the same text embedding approach to each video, along with the text of each question, results in one trajectory per video and one embedding coordinate (dot) per question (blue: Four Fundamental Forces; green: Birth of Stars; pink: general physics knowledge). Here we have projected the 15-dimensional embeddings into a 3D space using Uniform Manifold Approximation and Projection [UMAP; 19].

235 Analysis

236 Constructing text embeddings of multiple videos and questions

237 We extended an approach developed by [12] to construct text embeddings for each moment of each
238 lecture, and of each question in our pool. Briefly, our approach uses a topic model [3], trained on a
239 set of documents, to discover a set of k “topics” or “themes.” Formally, each topic is defined as a set
240 of weights over each word in the model’s vocabulary (i.e., the union of all unique words, across all
241 documents, excluding “stop words.”). Conceptually, each topic is intended to give larger weights
242 to set of words that appear conceptually related or that tend to co-occur in the same documents.
243 After fitting a topic model, each document in the training set, or any *new* document that contains at
244 least some of the words in the model’s vocabulary, may be represented as a k -dimensional vector
245 describing how much the document (most probably) reflects each topic. (Unless, otherwise noted,
246 we used $k = 15$ topics.)

247 As illustrated in Figure 6A, we start by building up a corpus of documents using overlapping
248 sliding windows that span each video’s transcript. Khan Academy videos are hosted on the

249 YouTube platform, and all YouTube videos are run through Google’s speech-to-text API [11] to
250 derive a timestamped transcript of any detected speech in the video. The resulting transcripts
251 contain one timestamped row per line, and each line generally corresponds to a few seconds of
252 spoken content from the video. We defined a sliding window length of (up to) $w = 30$ transcript
253 lines, and we assigned each window a timestamp according to the midpoint between its first
254 and last lines’ timestamps. These sliding windows ramped up and down in length at the very
255 beginning and end of the transcript, respectively. In other words, the first sliding window covered
256 only the first line from the transcript; the second sliding window covered the first two lines; and
257 so on. This insured that each line of the transcript appeared in the same number (w) of sliding
258 windows. We treated the text from each sliding window as a single “document,” and we combined
259 these documents across the two videos’ windows to create a single training corpus for the topic
260 model. The top words from each of the 15 discovered topics may be found in Table S2.

261 After fitting a topic model to each videos’ transcripts, we could use the trained model to
262 transform arbitrary (potentially new) documents into k -dimensional topic vectors. A convenient
263 property of these topic vectors is that documents that reflect similar blends of topics (i.e., documents
264 that reflect similar themes, according to the model) will yield similar (in terms of Euclidean distance,
265 correlation, etc.) topic vectors. In general, the similarity between different documents’ topic vectors
266 may be used to characterize the similarity in content between the documents.

267 We transformed each sliding window’s text into a topic vector, and then used linear interpo-
268 lation (independently for each topic dimension) to resample the resulting timeseries to once per
269 second. This yielded a single topic vector for each second of each video. We also used the fitted
270 model to obtain topic vectors for each question in our pool (Tab. S1). Taken together, we obtained
271 a *trajectory* for each video, describing its path through topic space, and a single coordinate for each
272 question (Fig. 6B). Embedding both videos and all of the questions using a common model enables
273 us to compare the content from different moments of videos, compare the content across videos,
274 and estimate potential associations between specific questions and specific moments of video.

275 **Estimating dynamic knowledge traces**

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

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

278 where

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

279 and where mincorr and maxcorr are the minimum and maximum correlations between any lecture
280 timepoint and question, taken over all timepoints and questions across both lectures and all three
281 question sets.

282 Intuitively, $\text{ncorr}(x, y)$ is the correlation between two topic vectors (e.g., the topic vector from one
283 timepoint in a lecture, x , and the topic vector for one question, y), normalized by the minimum and
284 maximum correlations (across all timepoints and questions) to range between 0 and 1, inclusive.
285 Equation 1 then computes the weighted average proportion of correctly answered questions about
286 the content presented at timepoint t , where the weights are given by the normalized correlations
287 between timepoint t 's topic vector and the topic vectors for each question. The normalization
288 step (i.e., using ncorr instead of the raw correlations) insures that every question (except the
289 least-relevant question) contributes some non-zero amount to the knowledge estimate.

290 **Creating knowledge and learning map visualizations**

291 An important feature of our approach is that, given a trained text embedding model and partic-
292 ipants' quiz performance on each question, we can estimate their knowledge about *any* content
293 expressable by the embedding model— not solely the content explicitly probed by the quiz ques-
294 tions. To visualize these estimates (Figs. 4, S1, S2, S3, S4, and S5), we used UMAP [19] to define a
295 2D projection of the text embedding space. Sampling the original 100-dimensional space at high
296 resolution to obtain an adequate set of topic vectors spanning the embedding space would be

297 computationally intractable. However, sampling a 2D grid is much more feasible. We defined a
 298 rectangle enclosing the 2D projections of the lectures' and quizzes' embeddings, and we sampled
 299 points from a regular 100×100 grid of coordinates that evenly tiled the enclosing rectangle. We
 300 sought to estimate participants' knowledge (and learning— i.e., changes in knowledge) at each of
 301 the resulting 10000 coordinates.

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

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

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

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

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

313 Testing the “smoothness” of knowledge

314 A core assumption of our modeling framework is that knowledge is “smooth” such that knowing
 315 about one concept implies knowledge about other related concepts (i.e., concepts that are nearby
 316 in text embedding space). Conversely, *not* knowing about a given concept implies *less* knowledge
 317 about other related concepts. We characterized how estimated knowledge (and lack of knowledge)
 318 fell off with distance in the text embedding space (Fig. 5, top panels).

319 For each participant, for each quiz, for each of c correctly answered question q in turn, we

320 sorted all of the other correctly answered questions in descending order of their topic vectors' 321 correlations with q 's topic vector. We repeated this for all correctly answered questions to obtain 322 a $c \times (c - 1)$ matrix of correlations, where the rows corresponded to held-out questions and the 323 columns corresponded to the most similar (leftmost column), second most similar (second column), 324 other correctly answered questions. Note that each correlation for each pair of questions (a and 325 b) appears exactly twice in this matrix: once when a is the held-out question, and once when b 326 is the held-out question. We applied the Fisher z -transformation to these correlations, averaged 327 down the rows, and then applied the inverse Fisher z -transformation to obtain a $1 \times (c - 1)$ array of 328 average correlations for the participant. We repeated this process across all n participants, yielding 329 an $n \times 14$ matrix (15 is the maximum number of questions that could have been answered correctly 330 on any single 15-question quiz, so at most 14 correctly answered questions could be compared to a 331 held-out correctly answered question). Note that some of the entries, for some of the participants, 332 were empty (e.g., if a given participant answered at least one question incorrectly, they would 333 never have 14 other correctly answered questions to compare to a held-out correctly answered 334 question). If a participant answered *no* questions correctly on a given quiz, their entire row would 335 be empty.

336 The blue ribbon plots in the top panels of Figure 5 display the mean (across participants) and 337 bootstrap-estimated 95% confidence intervals of these matrices (i.e., one per quiz, each plotted in a 338 separate panel). We repeated the same process for *incorrectly* answered questions (i.e., comparing 339 held-out incorrectly answered questions to other incorrectly answered questions from the same 340 quiz, for each participant in turn) to obtain the red ribbon plots in the top panels of Figure 5.

341 **Estimating held-out conceptual knowledge**

342 If we are able to accurately estimate a participant's knowledge about the content tested by a given 343 question, the estimated knowledge should have some predictive information about whether the 344 participant is likely to answer the question correctly or incorrectly. For each question in turn, for 345 each participant, we used Equation 1 to estimate (using all *other* questions from the same quiz, 346 from the same participant) the participant's knowledge at the held-out question's embedding

347 coordinate. For each quiz, we aggregated these estimates into two distributions: one for the
348 estimated knowledge at the coordinates of each *correctly* answered question, and another for the
349 estimated knowledge at the coordinates of each *incorrectly* answered question (Fig. 5, bottom
350 panels). We then used independent samples *t*-tests to compare the means of these distributions of
351 estimated knowledge.

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