Using the nested structure of knowledge to infer what others know

Edgar Dubourg, Thomas Dheilly, Hugo Mercier, Olivier Morin

Using the nested structure of knowledge to infer what others know.

Published at *Psychological Science*

Edgar Dubourg[1]*, Thomas Dheilly[1], Hugo Mercier[1†], Olivier Morin[1†]

[1]Institut Jean Nicod, Département d'études Cognitives, ENS, EHESS, PSL University, CNRS, Paris, France

†Co-last authors

Abstract

Humans rely on more knowledgeable individuals to acquire information. But, when we are ignorant, how to tell who is knowledgeable? We propose that human knowledge is nested: people who know only a few things tend to know very common pieces of information, while rare pieces of information are only known by people who know many things, including common things. This leads to the possibility of reliably inferring knowledgeability from minimal cues. We show that individuals can accurately gauge others' knowledgeability based on very limited information, relying on their ability to estimate the rarity of different pieces of knowledge, and on the fact that knowing a rare piece of information indicates a high likelihood of knowing more information in the same theme. Even participants who are largely ignorant in a theme can infer how knowledgeable other individuals are, on the basis of the possession of a single piece of knowledge.

Research Transparency Statement

General disclosures. Conflicts of interest: All authors declare no conflicts of interest. Funding: Agence Nationale de la Recherche (ANR) grant SCALUP- ANR-21-CE28- 0016-01 to Hugo Mercier. The authors also benefited from Agence Nationale de la Recherche grants ANR-17-EURE-0017 and ANR-10-IDEX-0001-02. Artificial intelligence: Authors occasionally used DeepL and GPT to translate sections of the supplementary materials from French to English. DeepL was used to assist with the initial translation, and GPT was used to enhance the readability of the translated text when necessary. No other artificial intelligence assisted technologies were used in this research or the creation of this article. Ethics: This research has received approval from a local ethics board: CER-Paris Descartes to HM (2019-03- MERCIER).

Study Disclosures. Preregistration: The hypotheses, predictions, data collection methods and statistical plans were pre-registered (https://osf.io/zwr4e) on 2024-02-08, prior to data collection (start date: 2024-02-12). There was no deviation from the preregistration, unless specified (see footnote 1). We also ran three pre-registered pilots (pre-registrations and results are available in SI). Materials: All study materials are publicly available (https://doi.org/10.17605/OSF.IO/5NFUE). Data: All primary data are publicly available (https://doi.org/10.17605/OSF.IO/YSZNE). Analysis scripts: All analysis scripts are publicly available (https://doi.org/10.17605/OSF.IO/NV76D). Computational reproducibility: The computational reproducibility of the results has been independently confirmed by the journal's STAR team.

Main Text

Humans acquire a tremendous amount of information from others, and in particular from those who are more knowledgeable than them. Efficient social learning requires identifying knowledgeable individuals–absent this ability, we risk acquiring false beliefs instead of knowledge. But, when we are ignorant, how can we tell who is knowledgeable? This is especially important in informal networks, which are crucial for the spread of information (e.g. about climate change, (1); more generally, see (2)), and in which people cannot usually rely on institutional markers such as profession. For instance, people can tell who, among their acquaintances, is more knowledgeable about politics (3), even though none of their acquaintances are political scientists. What cues do people use to draw such inferences?

Past research in adults has focused on indirect cues of knowledgeability: a confident intonation (4), answering quickly (5), being older (6), wearing glasses (7), or being paid attention to by others (8). There is a broad agreement that these cues are not very reliable and should only be used in the absence of better ones (9). Developmental research (for review, see 10) has shown that young children are able to infer who is knowledgeable based on a variety of cues, but these cues are either, as in adults, relatively unreliable (e.g. the speaker's accent, 11), or relatively coarse (e.g., who has visual access, 12; who is a well-established expert, 13, 14).

At least two strands of research predict that people should be skilled at inferring others' knowledgeability. The literature on epistemic vigilance (e.g., 15, 16) argues that since humans rely so much on communication, and since their interests regularly diverge, they must be endowed with efficient cognitive mechanisms to evaluate information provided by others, so as not to be misled, including mechanisms for evaluating relative knowledgeability. Relatedly, distributed cognition (e.g., 17, 18), in which people rely on others' knowledge to supplement their own shortcomings, also requires that people possess some ability to realize who is, or isn't, knowledgeable. In line with these predictions, we suggest that people are able to infer who is knowledgeable in a way that is reliable and relatively precise by leveraging two facts: that *knowledge is nested*, and information about *which pieces of knowledge are more common than others*.

Nestedness is a phenomenon, mostly studied in ecology, whereby sets either contain common and rare elements, or only common elements, but no set contains only rare elements (19). For instance, ecosystems with rare species also tend to contain common species, but species-poor ecosystems tend to contain only common species, not rare ones. Nestedness is not empirically trivial since it is entirely conceivable for a species-poor ecosystem to contain only rare species; and as a matter of fact, exceptions mean that nestedness is never perfect. Instead, nestedness is a continuous property for which various measures exist (20).

In formal terms (19), nestedness is a property of bipartite networks, i.e. of networks with two types of nodes, A and B (A could be ecosystems, and B, species), where A-type nodes only link to B-type nodes, and vice-versa. Such a network is nested to the extent that, for any set S of B-nodes that an A-node links to, and for any other set S' of B-nodes that another A-node links to, if S' > S, then S is included in S' (See Fig. 1). The abstract nature of nestedness makes it testable on datasets from different themes, such as economics (21), technology (22), and movie collections (23). This body of research suggests that nestedness is pervasive outside ecology, but not universal. For instance, Morin and Sobchuk (23) show that movie collections generally obey nestedness: movies present in small collections tend also to figure in bigger collections. However, some movie types systematically violate nestedness, being both rare and present only in small collections (e.g. noir).

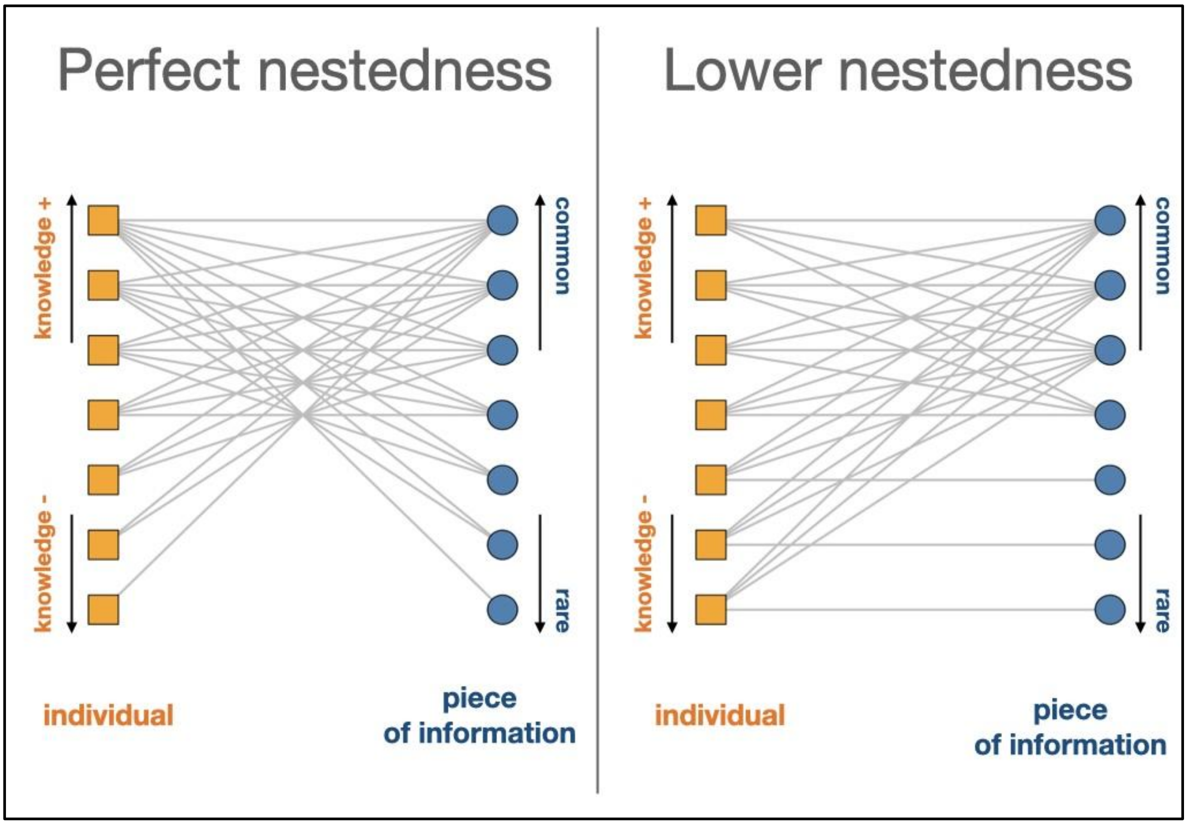

Fig. 1. A perfectly nested bipartite network (Left) contrasted with an imperfectly nested bipartite network (Right). In each bipartite network the yellow squares represent individuals and the blue circles the pieces of information they may or may not possess. In a perfectly nested network the most knowledgeable person knows everything that any less knowledgeable person knows. In a network with lower nestedness this is less true.

In the case of knowledge, each individual's mind can be thought of as a set of pieces of knowledge, some of which are more common than others. The possession of pieces of knowledge is nested to the extent that an individual who possesses a rarer piece of knowledge is likely to possess more common pieces of knowledge in the same theme. We can expect knowledge to be nested, for instance, if people tend to acquire more common pieces of knowledge first, before moving on to rarer pieces of knowledge (see, e.g., (24)), which might happen for a variety of reasons, related to the environment (curriculum design), or to content (if understanding rare pieces of knowledge requires common knowledge). Hence our first hypothesis:

H1 Human knowledge is nested.

If H1 is true, it follows that:

H1' People who know rarer pieces of knowledge tend to have more knowledge.

Although this hypothesis is a priori plausible, it isn't trivial. In many domains, understanding rare pieces of knowledge is not more difficult than understanding common ones—for instance, knowing the height of Mount Rakaposhi (the 26th highest peak in the world) is not conceptually more challenging than knowing the height of Mount Everest. As a result, it is possible for people to know rare pieces of knowledge while ignoring common ones. This might happen for instance in the case of savants, who possess very rare knowledge while lacking more common knowledge (for extreme cases, see, e.g., (25)). Even less trivial is the possibility that people's understanding of the nested nature of knowledge could be sufficient to use as a basis to infer how knowledgeable others are.

To use the (presumed) nestedness of knowledge in order to infer someone's knowledgeability from the fact that they possess a single piece of information, we must also be able to estimate how rare this piece of information is. That people are able to do this, even in domains they are not very familiar with, is far from obvious. For example, how can we tell whether more people know which is the first planet of the solar system, or which is the last? Here, we do not seek to elucidate the cues people might use to infer that a piece of knowledge is more or less rare. However, given the importance of evaluating others' knowledge for humans, we formulated the two following hypotheses, with H3 being made possible by H1 and H2:

> H2 Participants can accurately assess the rarity of pieces of knowledge.
>
> H3 If a participant knows someone else possesses one piece of knowledge, they can draw above chance inferences about that individual's knowledgeability in the relevant theme.

We tested H3 using the average performance of many participants (see below), and a good performance could therefore stem in part from the wisdom of crowds (26). H3 was thus also tested at the level of individual participants (H3p(articipant)).

The ability to infer others' knowledgeability is mostly useful for people who are not themselves knowledgeable, since it can help them acquire new knowledge and avoid false beliefs. As a result, we hypothesized:

> H2m(inimal) Even a participant who only has minimal knowledge in a theme can accurately assess the rarity of pieces of knowledge within that theme.
>
> H3m(inimal) If a participant who only possesses minimal knowledge in a theme knows someone else possesses one piece of knowledge, they can reliably infer that individual's knowledgeability in the relevant theme.

To test H2m and H3m, we relied on the fact that participants, after having estimated others' knowledge, were asked the same knowledge questions. These hypotheses were tested on the 30% of participants who were the least knowledgeable in the relevant domain.

Methods

We used three custom sets of 15 questions each, belonging to different themes (superheroes, American history, and astronomy, see Fig. 2B for examples, and SI for the complete list). Participants (N = 848, after exclusion, recruited online in the US, see SI for more information; Mean age = 43.9, SD = 13.08, 426 women, 422 men) were told about another participant (henceforth called the "virtual participant") who had answered one question correctly. First, they were asked how many participants, out of 100, they thought had answered that question correctly (reversed to yield *Estimated Rarity*, averaged over participants to yield *Average Estimated Rarity*, testing H2). Second, they were asked to indicate, for each of the remaining 14 questions, whether they thought the virtual participant—who had answered the initial question correctly—had also answered each of these questions correctly. Their responses were added to yield *Estimated Knowledge*, and averaged across participants and questions to obtain *Average Estimated Knowledge* (testing H3; see Fig. 2A). This procedure was repeated five times per participant, asking about a different virtual participant (having answered a different question correctly, randomly selected), all from the same theme (also randomly selected).

In a second step, each participant answered the 15 questions from the same theme. This allowed us to compute: *Actual Knowledge*, the share of correct answers each participant provided; *Average Actual Knowledge*, the mean Actual Knowledge of participants who correctly answered a given question; and *Actual Rarity*, the share of participants who incorrectly answered a given question (Fig. 2B; see SI for more information about the experimental design). All measures are normalized from 0 to 1 in the figures and the analyses. The design, hypotheses, and analyses were pre-registered (https://osf.io/zwr4e).

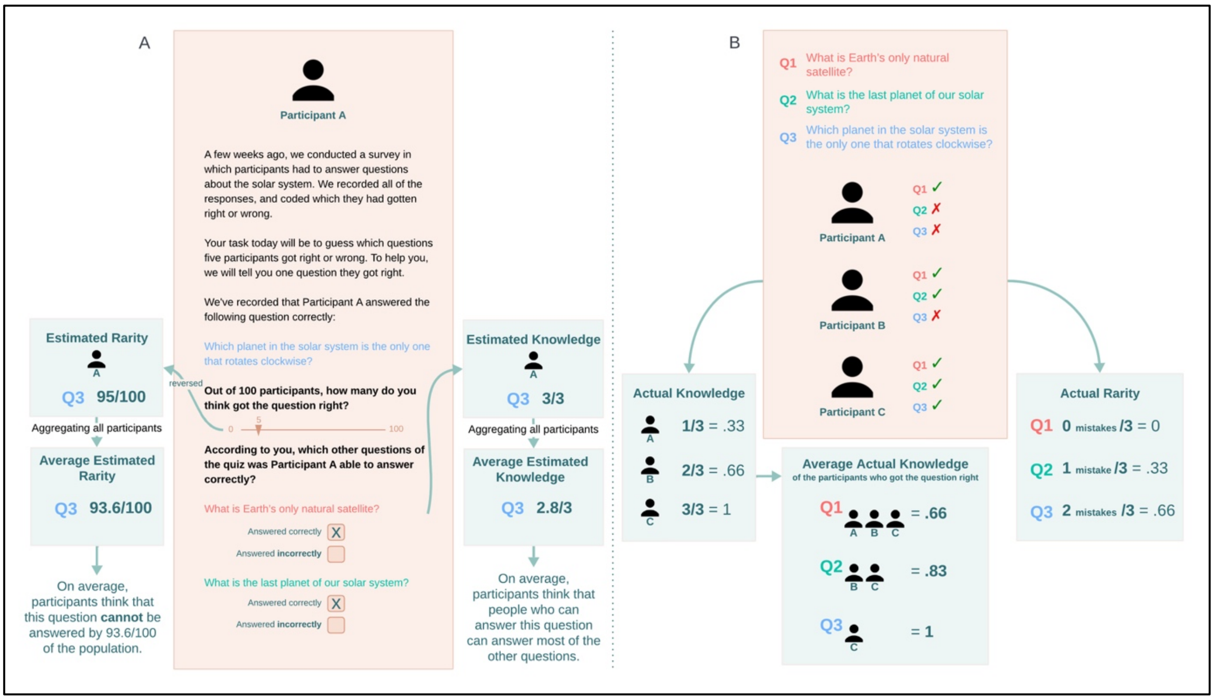

Fig 2. A: Participants estimate the knowledge of other individuals on a series of trivia questions, on the basis of their answer to a single trivia question, providing a measure of estimated knowledge. B: Participants answer the trivia questions themselves, providing a measure of actual knowledge. Depicted here are three questions from the astronomy theme; the actual experiments used 15 questions, and three different themes.

To test H1, we used nestedness measures standard in ecology (see SI and Results). To test all other hypotheses (H1', H2, H3, H3p, H2m, H3m), we used linear mixed-effects models with random intercepts either for Participant or for Theme, but not both (see Table 1). For H1', H3, and H3m, there is no need to include participant intercepts because we average across participants, so we include only the random intercept for Theme. For H2, H3p and H2m, we pre-registered models with one random intercept for Participant, to minimize the risk of non-convergence in more complex models. Since each participant was exposed to only one theme, we reasoned that most of the variance attributed to Theme would be accounted for by the Participant random intercept (but see SI for different model structure, providing comparable results to the one reported in the following section).

Hypothesis	**Model**
H1' The rarer a piece of knowledge is, the higher the knowledge of participants who possess it.	Average Actual Knowledge ~ Actual Rarity + (1|Theme)[1]

[1] Our pre-registration did not include a random intercept for Theme, but the model with the random intercept is more appropriate. The result of the model without the random intercept does not modify our findings (see open code, line 480).

H2 Participants can accurately assess the rarity of pieces of knowledge.	Actual Rarity ~ Estimated Rarity + (1|Participant)
H3 If a participant knows someone else possesses one piece of knowledge, they can infer that individual's knowledgeability in the relevant theme.	Average Actual Knowledge ~ Average Estimated Knowledge + (1|Theme)
H3p Same as H3 but at the individual level.	Average Actual Knowledge ~ Estimated Knowledge + (1|Participant)
H2m Even a participant who only has minimal knowledge in a theme can accurately assess the rarity of pieces of knowledge within that theme.	Actual Rarity ~ Estimated Rarity (by the least-knowledgeable 30% of participants in the relevant domain) + (1|Participant)
H3m If a participant who only possesses minimal knowledge in a theme knows someone else possesses one piece of knowledge, they can reliably infer that individual's knowledgeability in the relevant theme[2].	Average Actual Knowledge ~ Average Estimated Knowledge (by the least-knowledgeable 30% of participants in the relevant domain) + (1|Theme)

Table 1. The hypotheses tested in the study, alongside the corresponding statistical models used to assess them.

Results

All the hypotheses were verified (see Fig 3., and SI).

First (H1), knowledge was nested: two standard nestedness indicators, NODF and temperature, were more consistent with nestedness in each of the response's matrices corresponding to our three themes compared to randomized matrices preserving each question's difficulty and the participants' average accuracy (all six bootstrapped p-values = 0; number of iterations: 500). Nestedness implies (H1') that participants who were able to answer questions about rarer pieces of knowledge tended to perform better on the whole, which they were (H1': b = .39, p < .001, 95% CI [.32, .45]).

Second (H2), participants were able to reliably estimate the rarity of the pieces of knowledge associated with each question (H2: b = .54, p < .001, 95% CI [.51, .56]). We note, however, that participants tended to underestimate the difficulty of the least difficult questions.

Third (H3), participants, in the aggregate, were able to reliably estimate the Actual Knowledge of other participants (H3: b = 1.25, p < .001, 95% CI [1.04, 1.47]). Individual

[2] The results of a participant-level version of the same hypothesis (H3mp) are reported in the SI. The results were significant and coherent with the rest of the findings.

participants also performed better than chance when assessing the performance of other participants (H3p: $b = .26$, $p < .001$, 95% CI [.24, .28]).

H2 and H3 were also verified in the least-knowledgeable 30% of participants (H2m: $b = .45$, $p < .001$, 95% CI [.40, .51]; H3m: $b = 1.29$, $p < .001$, 95% CI [1.01, 1.57]; average number of questions these participants answered correctly, out of 15: superheroes = 2.8; American history = 1; astronomy = 3.5). We report in SI a series of pilot studies that tested a subset of these hypotheses, all yielding convergent results (including an analysis of a database containing over 42,000 participants and close to three million answers, confirming H1 (27), also demonstrating that knowledge is more highly nested within than across themes).

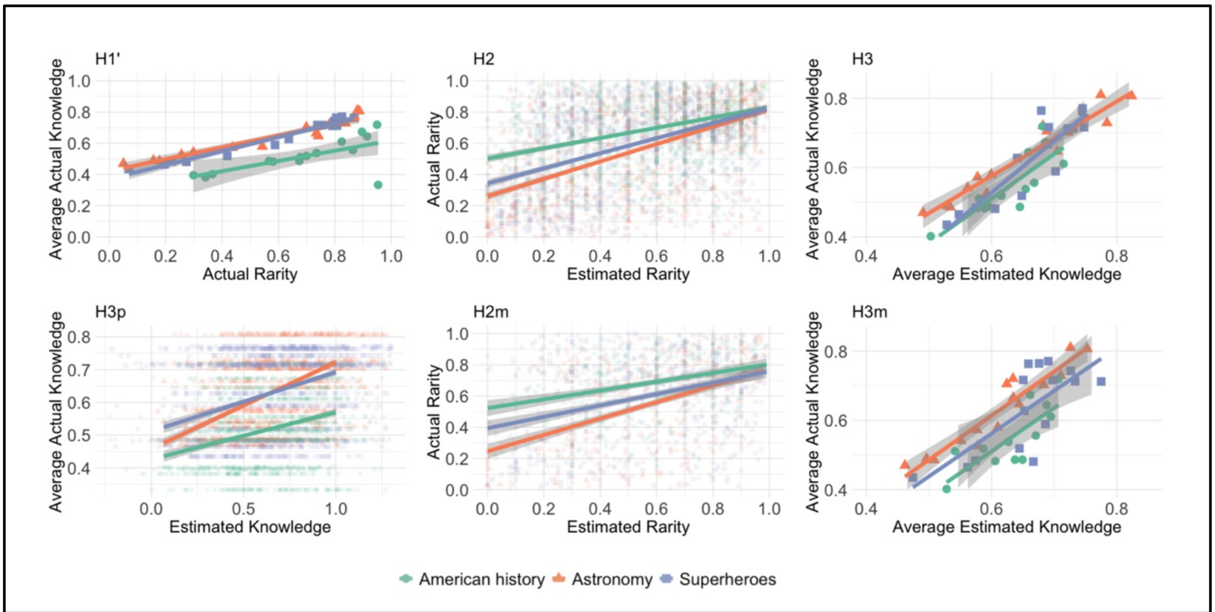

Fig 3. H1': As predicted if knowledge is nested, participants who answer questions with rarer answers (Actual Rarity) tend to be more knowledgeable (Average Actual Knowledge). H2: Participants are able to evaluate (Estimated Rarity) the rarity of the pieces of knowledge conveyed by each question (Actual Rarity). H3: Participants are in the aggregate able to evaluate (Average Estimated Knowledge) the performance of another participant from the fact that this other participant answered one question correctly (Average Actual Knowledge). H3p: The latter hypothesis holds at the level of individual participants (with Estimated Knowledge). H2m and H3m: H2 and H3 hold for the lower-performing 30% participants. For visual clarity, the lines in the figure represent independent linear regression models fitted separately for each Theme. The shaded areas around the regression lines indicate the 95% confidence intervals.

Discussion

Participants were able to infer other individuals' knowledgeability on the basis of the fact that these individuals possess one piece of knowledge. This is possible thanks to: (A) the fact that knowledge is nested, which we demonstrate in experimental data and in the analysis of a very large existing database of answers to trivia questions, and (B) participants' ability to tell how rare a piece of knowledge is.

In our experiments, participants were asked to estimate how many pieces of information out of 15 an individual knew, based solely on the fact that they had correctly answered one question. Nearly 50% of the participants (49% overall, 46% for the 30% least-knowledgeable participants) were within two points of the correct answer (from 0 to 15), showing a reasonable degree of accuracy (chance performance would be 23%), in light of the very limited information about that individual they could rely on, and of their own limited knowledge of the theme.

When the answers were aggregated, performance was extremely high (correlation between Average Estimated and Actual Knowledge: 0.86). Remarkably, this was also true of the least-knowledgeable participants (correlation between Average Estimated and Actual Knowledge: 0.75) who were nearly completely ignorant of the relevant theme—for instance, the 30% least-knowledgeable participants in American History, who on average only correctly answered one question out of 15.

The nestedness of human knowledge likely has several causes. Accessing or understanding some rare knowledge (e.g., of differential geometry) can require more common knowledge (e.g., of calculus). Failing to possess common knowledge in a domain might prove socially costly (e.g. not having read Shakespeare for an English professor more interested in contemporary authors). Historical contingencies such as the existence of canonical works or textbooks also channel learners into encountering some pieces of knowledge before accessing others. By contrast, other mechanisms might lead to non-nested patterns (e.g. in some groups possessing common knowledge, such as celebrity gossip, is seen as crass).

The present study suffers from some limitations. First, it could be expanded in scope in at least two ways: testing more themes of knowledge and replicating the results in different populations (representative samples, different cultures). Second, our analysis of the large existing dataset shows that nestedness drops between themes, so that someone who possesses rare knowledge in one theme isn't necessarily knowledgeable across all themes. In the present experiment, we restricted our questions within one theme, so that we do not know whether participants are sensitive to this distinction, or whether they tend on the contrary to attribute overly broad knowledgeability to those who possess rare pieces of knowledge in a theme (as might be suggested by theories of the evolution of prestige, 28). Third, although we observed that participants were able to accurately estimate the rarity of pieces of knowledge, we do not know how they did it. Future studies could address these limitations and shed further light on our ability to infer knowledgeability from minimal cues. We speculate that participants may assess the rarity of pieces of information on the basis of fast-and-frugal heuristics, such as the recognition heuristic (29), which in this case would consist in inferring a question's answer's frequency based on the frequency of certain words within it (e.g., questions about Batman are prima facie easier than questions about the lesser known Aquaman). The use of fast-and-frugal heuristics is consistent with the fact that less knowledgeable participants performed at least as well as more knowledgeable participants (29). Finally, we acknowledge that the mechanism we uncovered must have limits; in particular, the striking ability of novices to estimate the knowledgeability of others is bound to taper off at some point. For instance, all our participants have likely heard of superheroes, even if some are mostly ignorant in this theme; by contrast, someone who had never heard of superheroes might not have been able to draw any reliable inference in this theme.

Being able to infer others' knowledgeability on the basis of limited information might be more important than ever, as we are increasingly exposed to people we only see for a short while (time to read one social media post). However, the current informational environment also makes it easier for people to acquaint themselves with rare knowledge, even without possessing more basic knowledge. Future studies should investigate potential abuses of the otherwise reliable type of inference uncovered here.

References

(1) Goldberg, M. H., van der Linden, S., Maibach, E., & Leiserowitz, A. (2019). Discussing global warming leads to greater acceptance of climate science. Proceedings of the National Academy of Sciences, 116(30), 14804–14805. https://doi.org/10.1073/pnas.1906589116

(2) Katz, E., & Lazarsfeld, P. F. (1955). Personal Influence: The Part Played by People in the Flow of Mass Communications. https://www.routledge.com/Personal-Influence-The-Part-Played-by-People-in-the-Flow-of-Mass-Communications/Katz-Lazarsfeld-Roper/p/book/9781412805070

(3) Huckfeldt, R. (2001). The Social Communication of Political Expertise. American Journal of Political Science, 45(2), 425. https://doi.org/10.2307/2669350

(4) Brennan, S. E., & Williams, M. (1995). The Feeling of Another's Knowing: Prosody and Filled Pauses as Cues to Listeners about the Metacognitive States of Speakers. Journal of Memory and Language, 34(3), 383–398. https://doi.org/10.1006/jmla.1995.1017

(5) Richardson, E., & Keil, F. C. (2022). Thinking takes time: Children use agents' response times to infer the source, quality, and complexity of their knowledge. Cognition, 224, 105073. https://doi.org/10.1016/j.cognition.2022.105073

(6) Wood, L. A., Kendal, R. L., & Flynn, E. G. (2012). Context-dependent model-based biases in cultural transmission: Children's imitation is affected by model age over model knowledge state. Evolution and Human Behavior, 33(4), 387–394. https://doi.org/10.1016/j.evolhumbehav.2011.11.010

(7) Argyle, M., & McHenry, R. (1971). Do spectacles really affect judgments of intelligence? British Journal of Social & Clinical Psychology, 10(1), 27–29. https://doi.org/10.1111/j.2044-8260.1971.tb00709.x

(8) Henrich, J., & Gil-White, F. J. (2001). The evolution of prestige: Freely conferred deference as a mechanism for enhancing the benefits of cultural transmission. Evolution and Human Behavior, 22(3), 165–196. https://doi.org/10.1016/S1090-5138(00)00071-4

(9) Jiménez, Á. V., & Mesoudi, A. (2019). Prestige-biased social learning: Current evidence and outstanding questions. Palgrave Communications, 5(1), 20. https://doi.org/10.1057/s41599-019-0228-7

(10) Harris, P. L., Koenig, M. A., Corriveau, K. H., & Jaswal, V. K. (2018). Cognitive Foundations of Learning from Testimony. Annual Review of Psychology, 69, 251–273. https://doi.org/10.1146/annurev-psych-122216-011710

(11) Kinzler, K. D., Shutts, K., DeJesus, J., & Spelke, E. S. (2009). Accent Trumps Race in Guiding Children's Social Preferences. Social Cognition, 27(4), 623–634. https://doi.org/10.1521/soco.2009.27.4.623

(12) Pillow, B. H. (1989). Early understanding of perception as a source of knowledge. *Journal of Experimental Child Psychology*, *47*(1), 116–129. https://doi.org/10.1016/0022-0965(89)90066-0

(13) Danovitch, J. H., & Keil, F. C. (2004). Should You Ask a Fisherman or a Biologist?: Developmental Shifts in Ways of Clustering Knowledge. Child Development, 75(3), 918–931. https://doi.org/10.1111/j.1467-8624.2004.00714.x

(14) Lutz, D. J., & Keil, F. C. (2002). Early Understanding of the Division of Cognitive Labor. Child Development, 73(4), 1073–1084. https://doi.org/10.1111/1467-8624.00458

(15) Mercier, H. (2022). Not born yesterday: The science of who we trust and what we believe (First paperback printing). Princeton University Press.

(16) Sperber, D., Clément, F., Heintz, C., Mascaro, O., Mercier, H., Origgi, G., & Wilson, D. (2010). Epistemic Vigilance. Mind & Language, 25(4), 359–393. https://doi.org/10.1111/j.1468-0017.2010.01394.x

(17) Kameda, T., Toyokawa, W., & Tindale, R. S. (2022). Information aggregation and collective intelligence beyond the wisdom of crowds. Nature Reviews Psychology, 1(6), 345–357. https://doi.org/10.1038/s44159-022-00054-y

(18) Sloman, S., & Fernbach, P. (2017). The knowledge illusion: Why we never think alone. Riverhead books.

(19) Mariani, M. S., Ren, Z.-M., Bascompte, J., & Tessone, C. J. (2019). Nestedness in complex networks: Observation, emergence, and implications. Physics Reports, 813, 1–90. https://doi.org/10.1016/j.physrep.2019.04.001

(20) Almeida-Neto, M., Guimarães, P., Guimarães Jr, P. R., Loyola, R. D., & Ulrich, W. (2008). A consistent metric for nestedness analysis in ecological systems: Reconciling concept and measurement. *Oikos*, *117*(8), 1227–1239. https://doi.org/10.1111/j.0030-1299.2008.16644.x

(21) Bustos, S., Gomez, C., Hausmann, R., & Hidalgo, C. A. (2012). The Dynamics of Nestedness Predicts the Evolution of Industrial Ecosystems. *PLOS ONE*, *7*(11), e49393. https://doi.org/10.1371/journal.pone.0049393

(22) Mesoudi, A. (2021). Cultural selection and biased transformation: Two dynamics of cultural evolution. Philosophical Transactions of the Royal Society B: Biological Sciences, 376(1828), 20200053. https://doi.org/10.1098/rstb.2020.0053

(23) Morin, O., & Sobchuk, O. (2021). The shortlist effect: Nestedness contributions as a tool to explain cultural success. Evolutionary Human Sciences, 3, e51. https://doi.org/10.1017/ehs.2021.48

(24) Fastrich, G. M., & Murayama, K. (2020). Development of Interest and Role of Choice During Sequential Knowledge Acquisition. AERA Open, 6(2), 2332858420929981. https://doi.org/10.1177/2332858420929981

(25) Treffert, D. A. (2009). The savant syndrome: An extraordinary condition. A synopsis: past, present, future. Philosophical Transactions of the Royal Society B: Biological Sciences, 364(1522), 1351–1357.https://doi.org/10.1098/rstb.2008.0326

(26) Larrick, R. P., & Soll, J. B. (2006). Intuitions About Combining Opinions: Misappreciation of the Averaging Principle. *Management Science*, *52*(1), 111–127. https://doi.org/10.1287/mnsc.1050.0459

(27) Buades-Sitjar, F., Boada, R., Guasch, M., Ferré, P., Hinojosa, J. A., & Duñabeitia, J. A. (2022). The predictors of general knowledge: Data from a Spanish megastudy. Behavior Research Methods, 54(2), 898–909. https://doi.org/10.3758/s13428-021-01669-4

(28) Henrich, J., & Gil-White, F. J. (2001). The evolution of prestige: Freely conferred deference as a mechanism for enhancing the benefits of cultural transmission. Evolution

and Human Behavior, 22(3), 165–196. https://doi.org/10.1016/S1090-5138(00)00071-4

(29) Goldstein, D. G., & Gigerenzer, G. (2002). Models of ecological rationality: The recognition heuristic. Psychological Review, 109(1), 75–90. https://doi.org/10.1037/0033-295X.109.1.75