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Dilution of expertise in the rise and fall of collective innovation

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Diversity drives both biological and artificial evolution. A prevalent assumption in cultural evolution is that the generation of novel features is an inherent property of a subset of the population (e.g., experts). In contrast, diversity—the fraction of objects in the corpus that are unique—exhibits complex collective dynamics such as oscillations that cannot be simply reduced to individual attributes. Here, we explore how a popular cultural domain can rapidly expand to the point where it exceeds the supply of subject-specific experts and the balance favours imitation over invention. At this point, we expect diversity to decrease and information redundancy to increase as ideas are increasingly copied rather than invented. We test our model predictions on three case studies: early personal computers and home consoles, social media posts, and cryptocurrencies. Each example exhibits a relatively abrupt departure from standard diffusion models during the exponential increase in the number of imitators. We attribute this transition to the "dilution of expertise." Our model recreates observed patterns of diversity, complexity and artifact trait distributions, as well as the collective boom-and-bust dynamics of innovation.

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Introduction

"No one goes there anymore, it's too crowded"—a quote attributed to American baseball player Yogi Berra—captures a familiar sentiment when a trend becomes mainstream (Bentley and O'Brien, 2017). In the early, formative phase of a future trend, there is a high level of interest, creativity, and specialized expert knowledge among a small population of inventors (Rogers, 2010; Gladwell, 2006). As the trend becomes more widely adopted, the balance of invention versus imitation may tilt towards imitation: the copying of ideas through social-learning, rather than invention, i.e., the creation of new ideas. The change in this balance could occur when the popularizing trend extends beyond the population of experts, or people with enough specialized knowledge to make substantial changes to the trend.

These "expert" communities are often small compared to the mainstream. Fashion designers, for example, are much fewer than those who buy and sell clothes. The pioneers in Fortran programming and the original Internet in the 1970s are vastly outnumbered by users of computers and Internet in subsequent decades. Certain intellectual trends of philosophers or management scientists often become "mainstreamed" years later, via oft-repeated "buzzwords" of workplaces or political discourse. It may be that such a transition—when the imitation of new ideas outpaces the capacity of the expert community to feed in fresh ideas—could be a root cause of stagnant genres of popular culture, bloated bureaucracy, and the phenomenon known as "the death of expertise" (Nichols, 2017).

This issue connects to the literatures of cultural evolution, social economics, social-learning theory, complexity theory, and ecology. While each field employs concepts for the balance of imitation and invention, the terminologies can be inconsistent. Joseph Schumpeter (Schumpeter et al., 1939) defined *innovation* as the copying of unique *inventions*, whereas Frank Bass (Bass, 1969) used innovation to describe invention and *adoption* to describe the copying. The social-learning literature sometimes uses *producers* versus *scroungers* (Mesoudi, 2008), and the complexity science and business literature may use *exploitation* versus *exploration* (Axelrod and Cohen, 2008). Fortunately, all of these refer to the same distinction between the invention of something new versus the copying of those inventions. For this study, we will call the agents who invent new things *experts* and those who copy/adopt those inventions to be *imitators*.

Common to all these theories is that the balance of experts versus imitators is a crucial measure. Invention by experts produces new ideas, and imitation diffuses those ideas into the wider population. While population and community sizes vary, what matters is the proportion: if the majority are imitators rather than inventors, then ideas or technologies will persist through time. If the majority are experts, then there will be high turnover (Bentley et al., 2021; Eriksson et al., 2010). In fast-changing environments, it helps to have more expertise to adapt quickly, as too much imitation would allow outdated ideas to persist.

Invention is high in popular culture—a novelty-driven system (Vaesen and Houkes, 2021; Leroi et al., 2020; Lambert et al., 2020)—sustained by a high ratio of experts producing novelty for imitators to diffuse. Popular culture and trends change so fast that novelty in itself may be valued, as observed for video games (Montfort and Bogost, 2009), the cryptocurrency market (Park et al., 2020; ElBahrawy et al., 2017), and internet memes (Coscia, 2014, 2017). Elements of popular culture—video games, new stories, memes or jokes—often experience marginal returns, where the attraction declines with repeated use or repetition.

As the relative proportion of expertise needs to be high to generate so much novelty, we propose that the supply of experts cannot always keep up with the exponential increase in imitators during a fashion or fad (Rogers, 2010; Bass, 1969; Henrich, 2001; Bentley and Ormerod, 2009). Our hypothesis is that fashions that undergo a "boom-and-bust" dynamic —exponential growth in the number of products followed by a rapid decline—will exhibit a change when the ratio of experts to imitators abruptly declines: there is not enough specialized expertise to supply new inventions to the genre. We call this the "dilution" of expertise as opposed to its "death" (Nichols, 2017) because expertise still exists but is no longer abundant enough to maintain the same ratio versus imitation. Simple diffusion models (Bass, 1969; Henrich, 2001; Bentley et al., 2012), which *describe* the boom and bust cycle of fashions, replicate the number of adoptions for a single entity. These models typically rely on a fixed ratio of experts to imitators. Here, we explore how that expertise/imitation ratio decreases as a result of exponential growth in popularity in the first part of the diffusion curve. For this we employ a simple multi-component model of cultural production, which can connect the dynamics of diversity to the mechanistic generative processes of invention vs imitation. Ideas and technologies are complex systems (Buskell et al., 2019) encapsulating multiple elements, some of which may be well established, whereas others are perhaps used for the first time. Evolved products made entirely of novel elements are extremely unlikely (Dawkins, 1997), implying that new products are simply refinement and recombination of existing variants (Kandler and Laland, 2009).

We explore these effects in contemporary case studies of explosive trends from different decades: early personal computers and home consoles, Reddit posts, and cryptocurrencies. We characterize each case using established metrics of lexical diversity, information density, and structural complexity. We find evidence for a consistent increase in redundancy coupled with a decrease in information density and complexity in all case studies. Finally, we discuss the implications of this study for theories of the diffusion of information, social-learning, and cumulative cultural evolution.

Datasets

Our datasets include three boom-and-bust case studies, plus three additional case studies as controls, from different decades. The boom-and-bust examples are Atari 2600 video games in the 1980s, cryptocurrency documentation in the 2010s, and a Reddit r/Punpatrol posts, which began as a subreddit in 2018. As a control in each case, we use a contemporary dataset written in the same language and with similar purpose, structure and media. Atari 2600 is contrasted to Commodore Vic-20, an early home computer, which produced games in the same machine language and run in the same chipset. Cryptocurrency documentation in the form of white papers is compared to the evolution of scientific publications in the field of optics, both texts in English communicating mostly technical information in pdf documents structured in standardized sections. We also compare two Reddit communities or subreddits (r/PunPatrol and r/Politics), these are posts in topic-driven discussions incorporating english but also memetic communications. This amounts to six datasets of technological and cultural change.

We downloaded a collection of video game ROM cartridges for the Atari 2600 and Commodore Vic-20 from the websites www.atarimania.com and www.tosecdev.org, respectively. A custom reverse-engineering process recovered the set of assembly source codes from binary codes stored in $N = 738$ ROM files (see Supplementary Materials). Cryptocurrency "white papers" from the period 2009–2020 were collected from various online sources (whitepaperdatabase.com, allcryptowhitepapers.com, whitepaper.io) and dated according to their document production date when available or their first transaction otherwise. Presumably, many

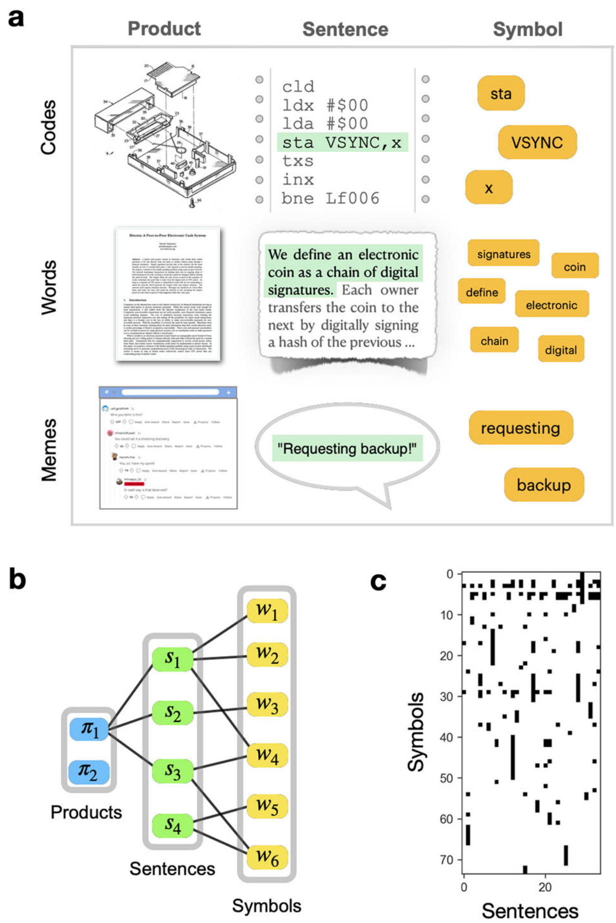

Fig. 1 Multi-scale structure of cultural products. a Many cultural artifacts have internal hierarchies that are formed by combining components or symbols (words, codes) into mesoscale structures (sentences), which then produce cultural goods or artifacts, i.e., video game cartridges, technical documentation, and social media memes (see text). **b** Formal representation of the hierarchical organization of cultural and technological knowledge: a product (blue) is a series of sentences (green) formed by words/symbols (yellow). **c** Bipartite network obtained from the sentence and symbol layer, each black filled square indicates when a symbol appears in a given sentence.

more cryptocurrency projects have existed, but documentation in the form of a parseable file could be found only for the $N = \sum N(t) = 1383$ included in this study. Bit strings were extracted from the pdf files from using the `Textract` library for Python. As a negative control for the cryptocurrency dataset, scientific publications from the period 1980–2020 listed by PubMed with the keyword "optics" were downloaded from their respective publication web resources. Pdf file processing was carried out as described for cryptocurrency white papers.

Reddit posts were retrieved using the Python Reddit API wrapper (`PRAW`) from their respective subreddits (r/PunPatrol and r/Politics). In these datasets, cultural products are $N = \sum N(t) = 10761$ collated posts and comments using a depth-first strategy, accumulated over a period of ≈330 days. All English bit strings were processed using the natural-language toolkit for Python (`NLTK`), and synsets were elaborated using the `WordNet` synonym sets by replacing each non stop-word with its most frequent synonym in the Brown corpus.

Overall, the datasets are of a diverse character (machine codes, text, and memes; see Fig. 1a), and they span time-scales ranging from days to years. Each case study involves a hierarchical structure of sentences formed of symbols (Fig. 1a) that can be represented as a three-layered multilayered network (Solé et al., 2002). Each layer represents a different type of element: product, sentence, and symbol (see Fig. 1b). Interactions between elements in adjacent levels are represented as a bipartite network (Fig. 1c).

Bipartite network representation of cultural products. The linear sequence of natural or artificial symbols were transformed into a bipartite network $B = (V, W, E)$ of symbols and sentences (see Fig. 1c). In a bipartite network, there is an edge $(v_i, w_j) \in E$ if the symbol $w_j \in W$ appears in the sentence $v_i \in V$. Using this data structure, we visualized how elementary ideas relate to each other and how complex the generative process of cultural products could be.

For natural-language texts, we separated the content by phrases, eliminated stop words using the Natural Language Toolkit Python library (NLTK) version 3.6.1 (Bird et al., 2009), and reduced it to semantically related words. This last step of the process was carried out using the WordNet synonym sets database (Miller, 1995; Ruiz-Casado et al., 2005), substituting each word by its most commonly used synonym using the Brown corpus and custom Python code. By collapsing the synonym space, we ensure that cultural products are represented by their relevant component ideas instead of considering different synonyms as culturally different elements. This approach has been previously used to more accurately quantify the cognitive extent of science (Milojevic, 2015) and provide a network evolution model of concepts in innovations (Iacopini et al., 2018).

At the most basic level, writing a video game consists in defining a sequence of 8-bit (byte) numbers encoding graphics, sound or instructions. For convenience, these machine codes have an equivalent lexicographic representation in a high-level assembly (Leventhal, 1986) language that follows a simple artificial grammar. This high-level representation allows for a natural partitioning of sentences and symbols, as well as a network reconstruction of their associations (see Supplementary Materials).

Methods

A dynamic model of cultural production. We used a modified Polya urn model (Mahmoud, 2008), following Tria et al. (Tria et al., 2014). This model represents the processes of invention and imitation as a sequential random sampling process from a common pool $\mathcal{U}$ of components, which reflect the collective know-how about basic ideas or technologies that facilitate new cultural production (see Fig. 2a). In this model, q and μ denote rates of imitation and expert invention, respectively, whereas $x(t)$ and $y(t)$ reflect the numbers of experts and imitators, respectively. Within this framework, cultural products are generated by assembling and recombining (Kandler and Laland, 2009; Lewis and Laland, 2012; Boyd et al., 2013) these basic ideas or technologies into larger cultural products of arbitrary length. During the sampling process, creators can encounter previously used components or new components (Fig. 2a light and dark boxes, respectively), corresponding to the processes of imitation and expert invention, respectively. Previously unused elements are attainable with the current shared knowledge. When a component is used for the first time, a quantity, $1 + \mu$, of different new elements is introduced in the urn, representing inventions adjacent to the ones just discovered, ready to be found by further sampling. Whenever a component is chosen, this signals its value to other creators, increasing, by amount q, the number of copies within the urn, and thus the likelihood that it will be used in the future.

To capture boom-and-bust dynamics, we have slightly modified the traditional Polya urn model by linking the urn parameters (q and μ) to a population of creators that fall into two categories: experts, $x(t)$, and imitators $y(t)$. Collectively, the

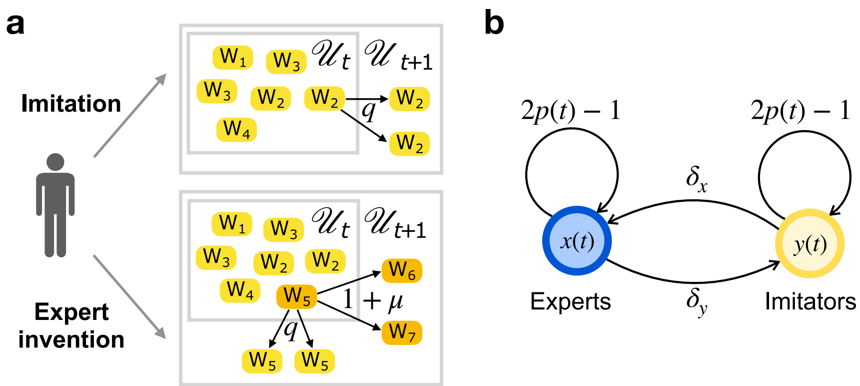

Fig. 2 A mathematical model of collective innovation. We simulate the process of cultural production using the Polya urn model. **a** At each time step t, an agent inspects the urn $\mathcal{U}_t$ and must decide between copying a pre-existing symbol ($w_2 \in \mathcal{P}$, top) or introducing a symbol that has never been used before ($w_5 \notin \mathcal{P}$, bottom). In each case, q copies of the chosen symbol are introduced in the urn $\mathcal{U}_{t+1}$ while inventions (at bottom) trigger $1+\mu$ other novelties (i.e., new symbols w_6 and w_7). **b** A population of experts $x(t)$ and imitators $y(t)$ is used as dynamic substrate for the urn exploration and reinforcement parameters (μ and q). These populations of agents are in turn coupled to the number of cultural products $N(t) = x(t) + y(t)$, assuming for the sake of simplicity that each agent produces one artifact per unit of time. Agents can switch strategies with some given probabilities (δ_x and δ_y). In both cases, the expected population growth ($2p(t)-1$) is a function of product novelty $p(t)$ at time t (see Supplementary Materials).

population creates new cultural products, $N(t)$, in an urn sampling process. For simplicity, we assume that each agent creates a single cultural artifact per unit of time: $N(t) = x(t) + y(t)$. When the population of experts, $x(t)$, increases, the number of new elements introduced into the common pool of knowledge also increases (i.e., μ is equal to the size of the population of experts). Similarly, a growing population of imitators enhances the processes of reinforcement, increasing q proportionately (i.e., q is equal to the size of the population of imitators). The population of imitators and experts can dynamically change following two main mechanisms (see Supplementary Materials). First, our agents are flexible creators (Miu et al., 2020): imitators can switch into experts and vice versa with rates δ_y and δ_x, respectively, as shown in Fig. 2b. Secondly, the overall population of creators grows and shrinks according to the expectation of success (Hirshleifer and Plotkin, 2021; MacKenzie, 1993; Van Lente and Rip, 1998; Kriechbaum et al., 2021), which is determined by the capacity of the system to produce novel cultural artifacts (i.e., containing new components). The probability $p(t)$ that at least one novel component has been found corresponds to the dynamics of success in an ideal uniform search (Doncieux et al., 2019):

$$p(t) = 1 - (1 - \Omega(t))^C$$

where C is the product size, and $\Omega(t)$ is the probability of sampling a new component at time t (see Supplementary Materials). The capacity for sustained innovation relates to the concept of open-endedness in cultural evolution, where the supply of new forms and components overcomes the limitations imposed by selection or reinforcement of cultural norms that promote stasis (Taylor et al., 2016).

Prediction of multi-scale diversity. We characterize cultural product diversity using three independent metrics: lexical diversity, information density, and product structural complexity. The Polya urn model of cultural production described above may predict cultural histories and, as a result, benchmarks for the evolution of these metrics under diverse situations of imitation and innovation. These metrics, as well as their boundaries and predicted behavior, are detailed in the following.

Assessment of lexical diversity. Lexical diversity measures the ratio of unique words (tokens) in a document to the total number of words in the document. We can estimate lexical diversity through the exponent of the Zipf's law (b), where the frequency of a word, $f(r)$, is predicted by its rank, r, in the frequency table as $f(r) \approx r^{-b}$. Lexical diversity becomes larger as the exponent b becomes smaller. However, linguistic studies have shown that natural texts display two different exponents in the rank-frequency distribution (Ferrer i Cancho and Solé, 2001; Gerlach and Altmann, 2013), corresponding to a kernel lexicon present in all communications, and another domain-specific lexicon at high ranks reflecting the topic and semantics of the communication (Piantadosi, 2014). In order to capture the topic-specific Zipf's law exponent b, a numerical fit of the tail of symbol frequency distribution (the last 1.5 orders of magnitude in rank) was carried out. The fit was produced using standard functions from the Numpy library for Python. The Polya urn model predicts that $f(r) \sim r^{-q/\mu}$ (Fig. 3a), where q and μ are the rates of imitation and expertise, respectively (Tria et al., 2014).

Compression-based measures of information density. Information density quantifies symbol sequence redundancy, or the amount to which repeated and organized symbol sequences may be reduced without losing information. Information density is calculated using an universal compression algorithm, Lempel-Ziv-Welch (LZW) that builds a word dictionary from the data stream being compressed (Ziv and Lempel, 1977) (see Supplementary Materials). Information density is defined formally as

$$\frac{L(x)}{L\log(|\alpha|)}$$

where $L(x)$ is the total binary code length of the compressed sequence, L is the cultural product size (measured in symbols), and α is the alphabet of symbols used in cultural products. When imitation q and invention μ are constant, the information density of modeled symbol sequences decays exponentially with each accumulated symbol count towards the theoretical entropy-production rate (Fig. 3b). This limit is high in diverse urns ($\mu > q$) and low in urns dominated by imitation ($q > \mu$).

Estimating structural complexity. Algorithmic complexity provides a robust measure for cultural randomness, and although uncomputable, it can be estimated by means of the Coding Theorem (Zenil et al., 2015). The more frequent a string x is, the

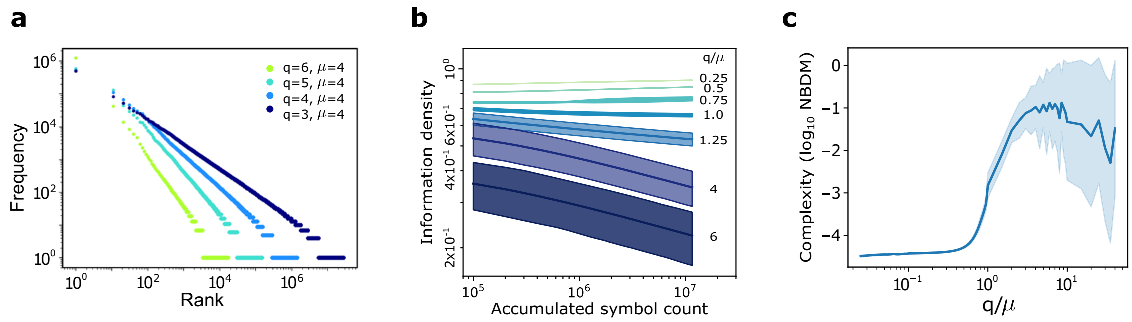

Fig. 3 Polya urn prediction of multi-scale diversity. a Rank-frequency distribution of components follows a power-law $f(R) \sim R^{-\alpha}$ with an exponent $\alpha \approx q/\mu$. Cultural products generated by urns with higher levels of imitation have steeper frequency rank distributions and so are less diversified. **b** When there is more imitation, synthetic histories become more compressible. We illustrate how the information density $\rho(n)$ increases when additional symbols are gathered for different values of q and μ. The solid line indicates the average information density in synthetic cultural histories, ρ, while the shaded region contains one standard deviation of the sample. **c** The plot of average log-transformed structural complexity (NBDM) as a function of the ratio q/μ demonstrates how imitation results in simpler networks. Solid line marks the average complexity for 10 replicates of each pair, $q \in [1, 40]$, $\mu \in [1, 40]$, plotted with logarithmic binning for the q/μ ratio. Shaded area represents 1 standard deviation of the sample. In each panel, simulated data comprise 10 independent synthetic cultural histories of 1000 products each, using different values of the urn parameters (q, μ) and the video game *Pac-Man* as a template.

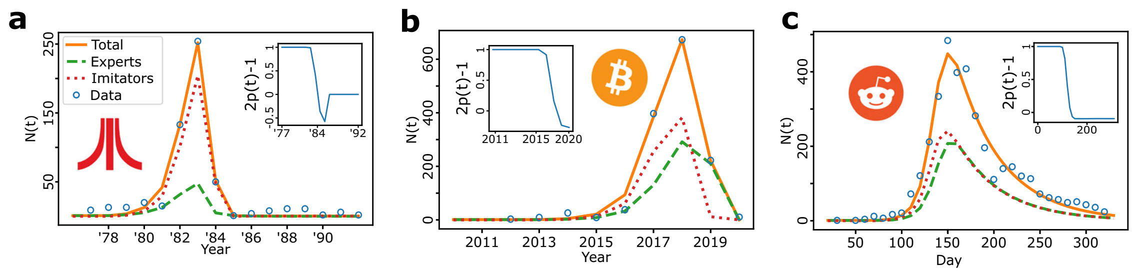

Fig. 4 Modeling the boom-and-bust pattern of cultural productivity. For **a** Atari 2600 video games, **b** cryptocurrencies, and **c** Reddit posts, we show the temporal dynamics predicted by the population-based model. We show the real cultural productivity, $N(t) = x(t) + y(t)$, during that period (open blue circles), the predicted cultural productivity (orange solid line) and the population of experts $x(t)$ and imitators $y(t)$ at any given time t (green and red dashed lines, respectively). As an inset for each case, we report the expected population growth $(2p(t) - 1)$ due to product novelty $p(t)$ in that period (see text).

lower its algorithmic complexity:

$$K(x) = -\log m(x) + O(1)$$

where $m(x)$ is the algorithmic probability that a random program generates the string. An exhaustive search can be used to estimate the complexity of small strings x. Instead of analyzing the complexity of sequences of symbols (computer instructions or text characters), we measure the complexity (Zenil et al., 2019) in the bipartite network B relating instructions/words and sentences. Block decomposition method (BDM) decomposes the adjacency matrix of the network B_i into smaller sub-strings σ_j (for which the Coding Theorem provides a complexity estimation). By putting together these local complexity values we obtain the structural complexity for the full network B_i:

$$\mathrm{BDM}(B_i) = \sum_{\sigma_j \in B_i} K(\sigma_j) + \log(N_j)$$

where N_j is the number of occurrences of the sub-string σ_j. Structural complexity of cultural products was computed using the `PyBDM` package, normalizing the block decomposition method metric using the size of the bipartite adjacency matrix $|B_i| = L$ and the size of the alphabet ($|\alpha|$):

$$\mathrm{NBDM}(B_i) = \frac{\mathrm{BDM}(B_i)}{L \log_2 |\alpha|}$$

This metric seeks the most straightforward generating strategy for recreating the network of how symbols (components) interact to form sentences (products). Intuitively, sentences that share one or more symbols have less structural complexity and display more redundancy. At modest degrees of imitation versus expert invention, we detect a peak in structural complexity (see Fig. 3c). When the degree of imitation is high ($q > \mu$), the resulting network is simple and contains a lot of redundancy owing to symbol repetition. When expertise is high ($\mu >> q$), the large number of unique symbols results in a sparse network with low complexity due to alphabet normalization.

Results

Boom-and-bust dynamics. The target datasets exhibit boom-and-bust dynamics, which are defined by a rapid or exponential rise in cultural and technological products followed by a rapid collapse. Figure 4 depicts the growth in numbers of cultural products versus the boom-bust pattern in estimated numbers of imitators and experts. Starting with a system composed of expert inventors, the interplay between cultural reinforcement and individual strategies dilutes their influence. Following an initial period of rapid diversity expansion, frequency-dependent imitation saturates the market with duplicate technologies and impedes experts' capacity to generate unique products, dramatically limiting the global pace of innovation. As estimated by our model, the abundance of imitators (dotted red line) is greatest for the Atari case (Fig. 4). Even if the population of experts (dashed green line) exceeds that of imitators (dotted red line) in the

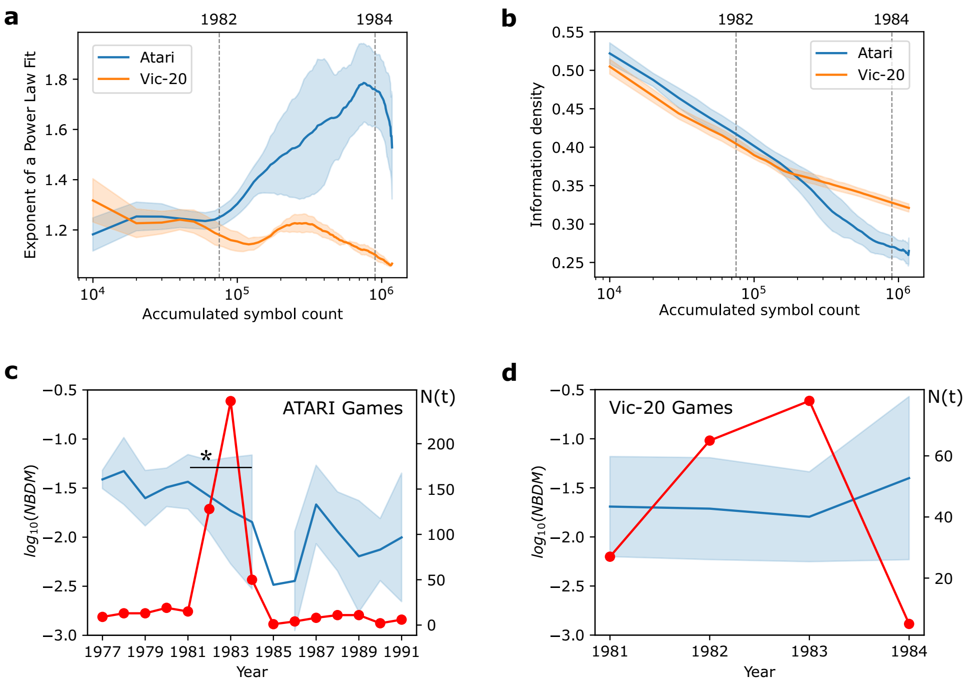

Fig. 5 Evolution of multi-scale diversity during the 1983 crash of video games. a Zipf's law exponent evolution for a given accumulated number of machine instructions in Atari 2600 (blue) and Commodore Vic-20 (orange). Solid line represents the average exponent of 25 replicate sub-samplings and shaded region encompasses 1 standard deviation of this distribution. **b** Decay of information density for the accumulated number of symbols $n(t)$ in Atari 2600 (blue) and Commodore Vic-20 (orange). Solid line represents the average information density of 25 replicates within-year orderings and the shaded region encompasses one standard deviation of the distribution. As a guide, vertical dashed lines mark the dates before (1982) and after (1984) the crash of Atari video games in panels **a** and **b**. The evolution of log-transformed size-normalized structural complexity (NBDM) in **c** Atari 2600 and **d** Commodore Vic-20 video games. Red line shows the cultural product diversity $N(t)$ in each domain for **c** and **d**. Asterisk-marked regions indicate statistically significant drops in complexity (see Supplementary Materials).

declining phase, the historical pattern of cultural-diversity loss cannot be reversed (see Fig. 4b).

Comparison between datasets and controls. Next, we analyze the time evolution of three multi-scale metrics presented above, namely lexical diversity through the Zipf's law exponent, information density and structural complexity. These metrics, as previously mentioned, are directly connected to the dynamics of imitators and experts: imitation-driven systems have lower richness (and a greater Zipf's exponent), lower information density, and lower structural complexity.

This analysis is shown in Fig. 5 for the Atari (blue line) and Commodore Vic-20 (orange line) datasets, with the latter serving as a control (using cumulative number of symbols on the x-axis for comparability). In the early stages of these systems, both datasets exhibit comparable Zipf's law exponents (Fig. 5a). However, there is a considerable increase in exponent values at the start of the exponential-growth phase (gray dotted line 1982), indicating an increase in the ratio (q/μ) of imitators to experts. Figure 5b displays the estimated information per machine symbol. The general pattern is consistent in the expected zone of expertise dilution, with Atari and Commodore systems separating immediately after the start of the boom and bust cycle. The decline in average complexity (blue curve) of Atari 2600 video games during peak cultural diversity (red curve) is shown in Fig. 5c, which is consistent with predictions for increasing imitation in a Polya urn generative process. In contrast, the average complexity of Commodore Vic-20 video games shows no temporal trend (Fig. 5d).

In Fig. 6 we explore structural patterns of cryptocurrency publications (blue line) compared to a scientific publication control dataset (orange line). The evolution of the Zipf's law exponent shows a departure from the control behavior starting at 2017 (Fig. 6a), when an explosion in redundant products took place. Information density paints a similar if attenuated trend, with scientific publications and cryptocurrency datasets displaying similar slopes in information density (Fig. 6b). By 2015, however, the addition of new symbols further reduces information density and increases redundancy. Later cultural products in the cryptocurrency dataset have increasingly more overlap with prior elements in the corpus. Finally, in the bottom-row panels we compare the normalized structural cultural product complexity for the two datasets. Whereas in optics publications the average complexity has not changed significantly in more than a decade (despite variations in the cultural productivity as shown by the red line), in cryptocurrency there is a significant decrease in complexity during the crash and in the year leading up to it.

Finally, the same analysis is carried out in the Reddit posts of two different communities. Whereas target (blue) and control (orange) datasets start at similar Zipf's exponent values (Fig. 7a), by day 120 (or 20,000 symbols) the cultural products in **r/PunPatrol** become significantly less rich in linguistic terms than their counterparts in **r/Politics**. In terms of normalized information density (Fig. 7b), **r/Politics** displays higher per symbol information than the **r/PunPatrol** dataset. Moreover, between days 130 and 150 there is a marked decrease in information density, signaling an enhanced redundancy of the posts produced during this period (which coincides with peak cultural productivity). We do not observe significant change in product complexity (Fig. 7c), which could be due to the short nature of the communications and thus the lack of a robust signal. In order to test this hypothesis, we analyzed the cultural complexity of the

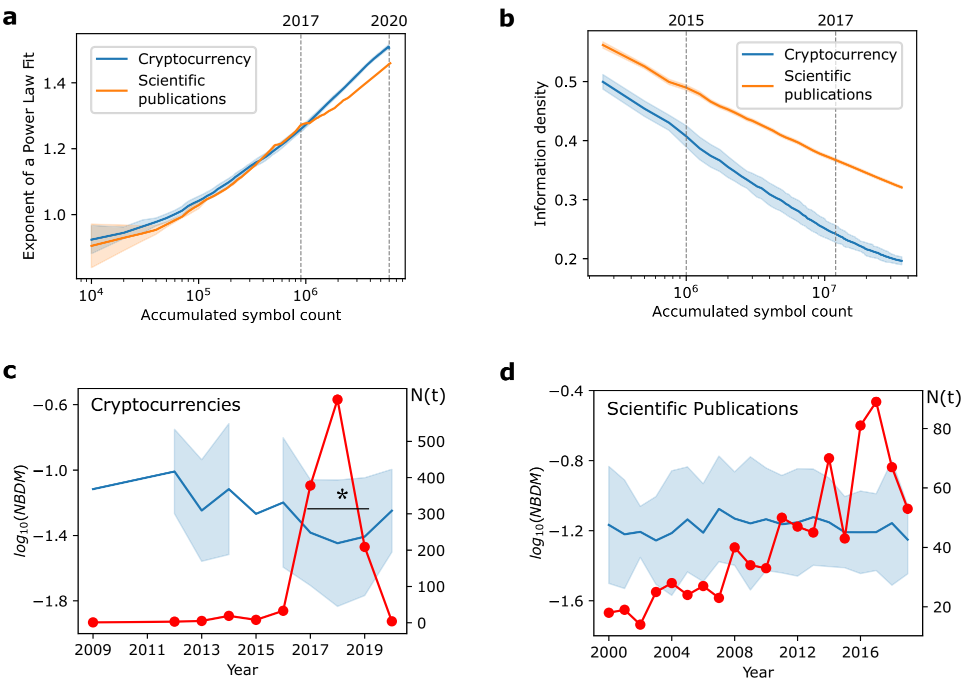

Fig. 6 Evolution of multi-scale diversity in the 2018 crash of cryptocurrencies. a Zipf's law exponent evolution for a given accumulated word count in cryptocurrency white papers (blue) and scientific publications (orange). Solid line represents the average exponent of 25 replicate sub-samplings, and shaded region encompasses one standard deviation of this distribution. **b** Decay of information density for the accumulated number of symbols $n(t)$ in cryptocurrency white papers (blue) and scientific publications (orange). The solid line is the average information density of 25 replicates within-year orderings, while the shaded region represents one standard deviation of the distribution. The evolution of log-transformed size-normalized structural complexity (NBDM) in **c** cryptocurrency white papers and **d** scientific publications. As a guide, the red line indicates the cultural product diversity $N(t)$ in each domain for **c** and **d**. Asterisk-marked regions indicate statistically significant drops in complexity (see Supplementary Materials).

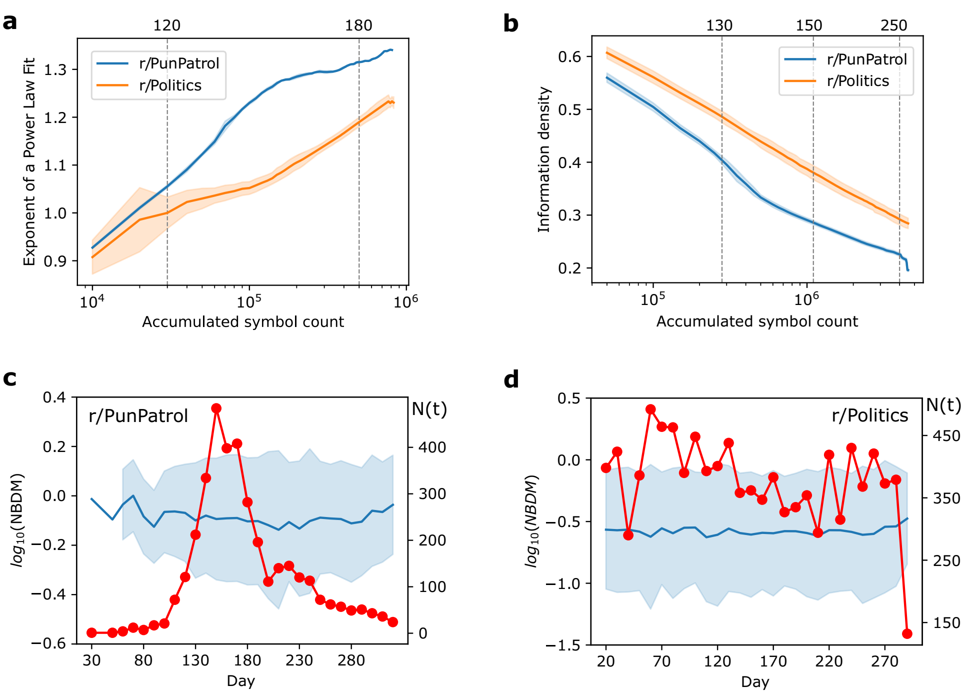

Fig. 7 Evolution of multi-scale diversity in the online communities. a Zipf's law exponent evolution for a given accumulated word count in the online communities r/PunPatrol (blue) and r/Politics (orange). Solid line represents the average exponent of 25 replicate sub-samplings, and shaded region encompasses one standard deviation of this distribution. **b** Decay of information density for varying number of accumulated symbols in the r/PunPatrol (blue) and r/Politics (orange). Solid line represents the average information density of 25 replicates within-year orderings, and the shaded region encompasses one standard deviation of the distribution. The evolution of log-transformed size-normalized structural complexity (NBDM) in **c** r/PunPatrol and **d** r/Politics. As a guide, the red line indicates the cultural product diversity $N(t)$ in each domain for **c** and **d**.

coarse-grained datasets, aggregating all posts in 10-day periods. The coarse-graining precludes us from performing statistical significance analyses but the aggregated product trend shows a marked decrease in structural complexity during the boom-and-bust period of **r/PunPatrol**, whereas **r/Politics** remains fairly constant (see Supplementary Material).

Discussion

Theoretical and empirical studies of cultural evolution assume that the frequency of cultural traits reflect the dynamics of selection and adaptation to changing environments (Lewis and Laland, 2012; Miu et al., 2018; Deffner and Kandler, 2019). Adaptability to a changing environment needs a steady supply of variation (Whitehead and Richerson, 2009; O'Brien and Shennan, 2010), but coalescing into few dominant forms or behaviors—cultural conformity (Claidière and Whiten, 2012)— is the necessary consequence of selecting the best solution discovered in a stable environment (Miu et al., 2018). This adaptive perspective describes the evolution of cultural and technological systems via domain-specific fitness functions (Mesoudi, 2008; Mesoudi and O'Brien, 2008; Caldwell and Millen, 2008; Thompson and Griffiths, 2021). An open question is how to incorporate the structural characteristics of cultural variants into theoretical models (Deffner and Kandler, 2019). When the cultural products involve complex encoding (for example, documents), any model that abstracts them with a small number of traits (or traits without interrelationships) may be unable to capture the cultural dynamics resulting from these interactions (Buskell et al., 2019) because the "relevant" cultural traits are identified a priori.

Here, we present a more a general framework using: (1) a data-driven approach, (2) a null model of recombination-based innovation, and (3) the notion of open-ended evolution. Our framework avoids abstract (or simplified) representations of cultural products. Instead, we directly monitor multi-scale diversity in cultural products naturally encoded with symbols (code or words). Although networks have been employed in cultural-evolution research, such as when modeling the social dynamics of innovation (Cantor et al., 2021; Derex and Mesoudi, 2020), using networks to capture the complexity of cultural products is far less frequent (Valverde et al., 2002; Buskell et al., 2019). In order to avoid idiosyncratic results due to the choice of metrics or scale of analysis, we propose a more general approach that encompasses multiple measures of diversity: lexical diversity, information density and structural complexity. More accurate and reliable estimates of imitation and innovation rates should be possible if representation biases are reduced.

Previous work has shown the build-up of cumulative culture is more dependent on the combination of existing components than on the introduction of unique products (Kandler and Laland, 2009; Lewis and Laland, 2012; Boyd et al., 2013; Valverde and Sole, 2015), as well as the global impact of component diversity when developing technological products (Hidalgo and Hausmann, 2009). Similarly, our null model generates synthetic products by the recombination of existing components (imitation) with new ones (expert invention). We have shown that the generative approach makes testable predictions in real-world systems, most notably the emergence of multi-scale diversity with the imitation-to-invention ratio, which changes dynamically within the population (Fig. 2b).

Another key feature is a dynamical motif of cultural productivity: the exponential growth followed by an equally rapid collapse, commonly referred to as boom-and-bust (see Fig. 4). Prior work has usually explained this dynamical feature by including exogenous effects: environmental degradation (Butzer, 2012), changes in carrying capacities, mismanagement of expectations (Hirshleifer and Plotkin, 2021) or hype (Kriechbaum et al., 2021). Here, we connect the decline in cultural productivity with the dilution of expertise, which highlights how the supply of experts affects growth and innovation.

In prehistory, cultural evolution was slower in tempo, with technological stability across lengthy periods of time (O'Brien and Shennan, 2010). However, recent times have been dominated by the persistent search for novelty, keeping the diversity and complexity of technologies growing over large time-scales (Duran-Nebreda and Valverde, 2023). This is the defining trait of open-ended evolution (Taylor et al., 2016), the characterization of an evolutionary process as the endless new adaptations to a changing environment instead of stability. These evolutionary dynamics are reminiscent of the novelty-search algorithm (Lehman and Stanley, 2008), which suggests a new interpretation of cultural evolutionary processes not based on the selection of specific traits, but by the creation and maintenance of diversity. The successful application of novelty-search algorithms to complex engineering challenges exemplifies this idea (Lehman and Stanley, 2011), indicating how we can expand the theory of cumulative cultural evolution to comprehend the origins and consequences of cultural diversity and transmission biases. Our study highlights that the explicit search for novelty is an under-appreciated component of the theory of cumulative cultural evolution (Gabora, 2019).

Finally, the framework described here serves as a starting point for system-specific analyses, including additional constraints regarding the effects of memory and more sophisticated population structure (Gleeson et al., 2014; Bentley et al., 2014; Kandler and Crema, 2019). Future research should build on our theoretical predictions to create a system of "early warning signals", which can be used to actively monitor excessive imitation and, hopefully, lessen the economic impact of expertise dilution.

Data availability

Example scripts for the methods described above, as well as processed datasets, may be obtained from the open repository at the following link: https://figshare.com/projects/Dilution_of_expertise_in_the_rise_and_fall_of_collective_innovation/141851.

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Author contributions
SD-N and SV conceived the research, SD-N and SV conducted the experiments, SD-N, MJO, RAB, and SV analyzed the results. All authors wrote, reviewed, and accepted the final manuscript.

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The authors declare no competing interests.

Ethical approval
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Informed consent
This article does not contain any studies with human participants performed by any of the authors.

Additional information

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