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Quantifying the Selective Forgetting and Integration of Ideas in Science and Technology

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How long will this article be remembered? How long will people reference it in their conversations, and for how many years will other authors cite its findings in their own works? A community's attention to a cultural object decays as time passes, a process known as collective forgetting. Recent work models this decay as the result of two different processes. One linked to communicative memory—memories sustained by human communication—and the other linked to cultural memory—memories sustained by the physical recording of content. Collective forgetting has significant impacts on communities, yet little is known about how the collective forgetting dynamic changes over time. Here, we study the temporal changes of collective memory and attention by focusing on two knowledge communities: inventors and physicists. We use data on patents from the United States Patent and Trademark Office (USPTO) and physics papers published by the American Physical Society (APS) to quantify those changes over time. The model enables us to distinguish between two branches of forgetting. One branch is short-lived, going directly from communicative memory to oblivion. The other branch is long-lived, going from communicative memory to cultural memory before going on to oblivion. The data analysis shows an increase in the forgetting rate for both communities as the amount of information in each of them grows. That growth of information forces knowledge communities to increase their selectivity regarding what is stored in their cultural memory. These findings confirm the forgetting as annulment hypothesis and show that knowledge communities can slow down collective forgetting and improve selectivity processes.

Public Significance Statement

At any historical moment, many different scientific ideas are floated, tested, repudiated, repeated, and reinforced. As a society, the further we get from the birth and manipulation of an idea, the more likely we are to forget it until we reach a point where we are left only with the thoughts that we collectively decided are worth remembering. Yet, within this sheaf of ideas in time, the processes associated with ideas that have staying power remain a mystery. In this study, we statistically modeled behavioral processes of communal forgetting, filtering, and factualism using large bibliographic databases on scientific publications and technological inventions that allow us to track the referencing of ideas and technology over time. The model identifies and distinguishes rapid forgetting – ideas and technology that are forgotten after their birth even if they had initial popularity, and long-lived forgetting – ideas and technology that slowly fade from memory. We find that collective forgetting acts like an annulment process. As information grows, forgetting rates increase despite the growing capacity to store and reference information. Further, our

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model of the forgetting process finds that sticky ideas and technology are selective rather than representative of the sheaf of ideas that were popular, and that the selectivity of ideas within the community of practice changes over time.

Keywords: collective attention, collective memory, collective forgetting, mathematical modeling, computational social science

Collective attention—understood as a measure for various forms of population-level content consumption patterns (Candia et al., 2019; Lorenz-Spreen et al., 2019; Wang et al., 2013)—is of central importance to decision-making processes as well as the spread of ideas and information. However, most of the progress in the study of collective attention has been made in small laboratory studies and on the theoretical literature strand of attention economics (Falkinger, 2007; Ocasio, 1997; Simon, 1971). Though psychologists (Kahneman, 1973; Pashler, 1998), economists (Camerer, 2003), and marketers (Dukas, 2004; Pieters et al., 1999; Reis, 2006) have studied it at the individual and small-group level (Wu & Huberman, 2007), research is short on quantitative models that can connect it empirically to large-scale data and answer questions about the mechanisms that drive temporal changes in collective attention in diverse communities (Fortunato et al., 2018).

However, recently developed models of the adoption and diffusion of cultural content enable investigation into two mechanisms central for collective attention dynamics (Candia et al., 2019; Csárdi et al., 2007; Dorogovtsev & Mendes, 2000; Golosovsky & Solomon, 2012; Higham et al., 2017a, 2017b; Valverde et al., 2007; Wang et al., 2013): cumulative advantage and temporal decay. Cumulative advantage (Albert & Barabási, 2002; Barabási & Albert, 1999; Merton, 1988; Price, 1976; Yule, 1925) refers to a process in which future attention grows as a function of cumulative attention in a manner similar to the way wealth begets more wealth. In this line of inquiry, that takes the form of a compounding increase in the number of people engaging with a given cultural piece. This manner of growth is offset by temporal decay processes driven by competition from other cultural products and the limited capacity and/or reduction of the public's collective attention (Falkinger, 2007; Lorenz-Spreen et al., 2019; Soderstrom et al., 2016; Wu & Huberman, 2007). These two mechanisms shape collective attention. While the cumulative advantage mechanism is well understood, the temporal decay mechanism is not, primarily because of the ongoing debate about the statistical rates at which attention decays (Candia et al., 2019; Higham et al., 2017a, 2017b; Stringer et al., 2008, 2010; Wang et al., 2013).

This work uses a computational social science approach and recently available data sets of millions of observations noted in the citations in published scientific works and inventors' citations in patents. Thus, we measure collective memory processes and community dynamics to quantify the collective behavior of scientists' and inventors' communities concerning the variations of collective attention and memory over time. As Halbwachs stated in 1925, "The idea of an individual memory, absolutely separate from social memory, is an abstraction almost devoid of meaning" (Connerton, 1989; Halbwachs, 1992).

A community's cultural context includes ideas, behaviors, knowledge, skills, and innovations that can change, be transferred, and be forgotten over time in a process called cultural evolution (Cavalli-Sforza & Feldman, 1981; Creanza et al., 2017). That forgetting has important consequences in communities. For instance, evidence from cultural evolution literature suggests that the drastic reduction in the number of people (apprentices) in a community leads to technological and cultural oblivion. For instance, in Tasmania, where knowledge of bone tools has been lost (Henrich, 2004), as well as at Torres Island in the Vanuatuan Archipelago in Oceania, where methods of canoe construction have been forgotten (Rivers & Smith, 1926). Similar patterns of remembering and extending ideas have been shown to exist in science between mentor and mentee relationships (Ma et al., 2020; Malmgren et al., 2010; Mukherjee et al., 2017).

A reduction in the number of people in a community reduces that community's collective attention and collective memory size to store its cultural information. Similarly, an excess of information forces communities to focus their collective attention on specific subgroups of cultural pieces, leading to a faster forgetting. This oblivion process is named as forgetting as annulment (Connerton, 2008). Here, we empirically test the forgetting as annulment process, i.e., if the excess of information promotes oblivion in inventors' and physicists' communities. Then we explore how these communities actively react to the changes in the amount of information that they produce.

Collective Memory

Collective memories are all the memories, knowledge, and information preserved by a community and help shape its identity (Hirst & Manier, 2008; Mukherjee et al., 2017). The community may be as big or small. For instance, a nation's collective memory may be sustained by messaging in its media and educational system. In contrast, the collective memories of a family may be sustained by their dinner conversations and pictures. In the case of scientists and inventors, memories—significant discoveries or inventions—may be sustained by talking at conferences and writing and reading

Cristian Candia

formal documents. In general, communities sustain collective memories by two mechanisms: communicative memory (i.e., oral communication) and cultural memory (i.e., access to information records).

For decades, scholars studying collective memory have advanced a large number of definitions, mechanisms, and processes that help characterize its different forms as well as key features that contribute to its preservation (Hirst et al., 2018). Indeed, from the literature, we can identify two types of collective memories characterized by how they are remembered. Assmann organizes actively remembered knowledge (Assmann, 2008) with two concepts: the canon—"actively circulated memory that keeps the past present" (p. 98), and the archive—"passively stored memory that preserves the past" (p. 98). Memory studies scholars have extensively argued that culture is inextricably linked to memory (Assmann, 1995; Halbwachs, 1992, 1997) and its counterpart, forgetting (Assmann, 2008). Assmann (1995) also defines the existence of two modes of cultural memory

> . . . the mode of potentiality of the archive whose accumulated texts, images, and rules of conduct act as a total horizon, and . . . the mode of actuality, whereby each contemporary context puts the objectivized meaning into its own perspective, giving it its own relevance. (p. 130)

Collective memory is primarily shaped by communicative acts (e.g., conferences) that focus the attention of specific communities on specific pieces of knowledge (Candia et al., 2019). Cultural pieces that receive most of the collective attention live in a mode of actuality (Assmann, 1995) and form part of the canon (Assmann, 2008) and their current interpretation is part of the community's identity (Mukherjee et al., 2017).

From the cognitive psychology strand of literature, we can define an intermediate level between the mode of actuality and the mode of potentiality that is mainly shaped by accessing records (e.g., searching literature). Access can be related to both top-down and bottom-up mechanisms. Top-down mechanisms depend on the existing context of the community (Hirst et al., 2018) and how it contributes to the formation and retention of collective memories in the form of familiarity (Roediger & DeSoto, 2016; Rubin, 1995), narrative templates (Hammack, 2011; Wertsch, 2002), and cultural attractors (Buskell, 2017; Richerson & Boyd, 2005; Sperber & Hirschfeld, 2004). For instance, familiarity increases the memorability of events and can even cause false memories. Narrative templates, which are schemata through which people describe multiple historical events, can also shape memories, such as the collective Russian memory of Russian exceptionalism that emerged from the narrative template of invasion, near defeat, and heroic triumph in the second world war (Wertsch, 2002). Cultural attractors, such as repetitive children's songs or count-out rhymes, can increase the preservation of memories across generations (Rubin, 1995), such as the way the song "Dixie" preserves the false memories of The Lost Cause.

Bottom-up mechanisms depend on microlevel psychological processes that drive social outcomes (Hirst et al., 2018) such as retrieval-induced forgetting (Cuc et al., 2007; Garcia-Bajos et al., 2009; Storm et al., 2012) and social affinities that increase the mnemonic power of conversations (Coman & Hirst, 2015; Coman et al., 2014; Echterhoff et al., 2009; Stone et al., 2010).

Finally, according to Assmann, passively stored memories exist in a mode of potentiality (Assmann, 1995). They are stored in an archive and are not part of the community's current conversation but can be retrieved if the community decides to recall those pieces. All forms are dynamic "Elements of the canon can . . . recede into the archive, while elements of the archive may be recovered and reclaimed for the canon" (Assmann, 2008, p. 104). This process creates potential temporal changes that are not yet quantified in a model that unifies integrating and forgetting ideas in science and technology.

A Computational Social Science Approach

Computational social science has used big data methods to study the actuality mode (Assmann, 1995) of memories, focusing its efforts on the consumption of cultural content from Wikipedia page views (Candia et al., 2019; García-Gavilanes et al., 2017; Jara-Figueroa et al., 2019; Kanhabua et al., 2014; Skiena & Ward, 2014; Yu et al., 2016), scientific paper and patent citations (Candia et al., 2019; Higham et al., 2017a, 2017b; Mukherjee et al., 2017; Uzzi et al., 2013; Wang et al., 2013), and the effects of accomplishments, technology, language, and triggers in the dynamics of collective memory and attention (Bowker, 2005; Ferron

Brian Uzzi

& Massa, 2014; García-Gavilanes et al., 2017; Jara-Figueroa et al., 2019; Kanhabua et al., 2014; Ronen et al., 2014; Yu et al., 2016; Yucesoy & Barabási, 2016). For instance, on a broad societal scale, it has been shown that people forget the past at a rate that increases as time passes (Michel et al., 2011). Further exploration shows that changes in communication technologies such as the rise of the printing press, radio, and TV have been shown to affect attention since researchers can correlate them with changes in occupations present in the community when these technologies emerge (Jara-Figueroa et al., 2019).

Consequently, the computational social science approach easily accommodates Assmann's definition of collective memory (Assmann 1995, 2011), which focuses on the cultural products that communities remember, differentiating the modes of actuality (i.e., actively remembered content sustained by communicative and cultural memory) and potentiality (i.e., passively stored content that has the chance to come back to actuality if the community decides to restore these memories).

Recently, Candia et al. (2019) introduced a mathematical and empirical model of the effect of time on collective memory (separating it from the well-known effect where attention begets attention) and the generalization of this decay function to a variety of data sets and domains such as songs, movies, biographies, papers, and patents. This research contributes to understanding the functional forms governing the average temporal decay of collective memory over long periods. The generalization of these forms to multiple cultural domains reveals a remarkable degree of universality. Thus, the functional form of the temporal decay is the same regardless of year, accumulated attention, or cultural domain.

Here, we use this model to investigate two properties of the dynamics of collective memory and attention. First, we explore the forgetting as annulment hypothesis that states that an excess of information promotes forgetting. Second, we explore how the communities' reactions to changes in the amount of information are the same for different types of cultural productions, in this case, patents and scientific papers.

Analysis

We use the collective memory and attention model proposed by Candia et al. (2019) that has been tested on different cultural domains such as music, movies, patents, and papers (Candia et al., 2019). The model requires to account for cumulative advantage effects to isolate the temporal pattern of collective memory and attention. Then, we use the model to fit this pattern characterized by different attention levels: an initial phase of high attention followed by an extended and slower phase of forgetting. These two temporal phases are associated with collective memory (Assmann, 2008, 2011; Candia et al., 2019; Erll, 2011; García-Gavilanes et al., 2017; Goldhammer et al., 1998; Halbwachs, 1997; Roediger et al., 2009; Roediger & DeSoto, 2014; Rubin, 2014; Wertsch, 2002; Zaromb et al., 2014). They can be divided into two mechanisms: communicative memory (oral transmission of information) occurring right after the release of a cultural product, and cultural memory (accessing the physical recording of information) that are subsequently established.

We study the temporal dynamic of collective memory and attention of inventors' and physicists' communities in the United States by fitting the model to data from the U.S. Patent and Trademark Office (USPTO; see Appendix A for a patent example) and the American Physical Society. We explicitly calculate the rates at which information is forgotten each year to inspect how temporal changes in forgetting are related to the amount of information produced by American inventors' and physicists' communities.

The Model

We model the temporal dimension of collective attention in a two-step process. We assume that initially, all the attention that a cultural document receives comes from communicative acts. Then, as time passes, the attention received is given by the sum of the collective attention created by communicative memory and cultural memory, with the first sustained by oral transmission and the second by accessing information records (Candia et al., 2019).

The expected collective attention decreases as time advances. Figure 1A diagrams the model in which both communicative and cultural memories coexist but decay at different rates and in which attention sustained by communicative acts decays faster than the accessing of records. In the beginning, most of the collective attention comes from communicative memory (u). Then it decays by following two pathways toward oblivion. Branch 1 goes from communicative memory (u) to oblivion at a rate of p, which means that all the attention that decays on Branch 1 is lost. Branch 2 goes from communicative (u) to cultural (v) memory at a rate of r, and then to oblivion at a rate of q, indicating that part of the attention sustained by communicative acts is then sustained through the accessing of records. Cultural pieces following Branch 2 spend more time in a mode of actuality, leading them to be the target of collective attention for a longer time. We note that the three decay rates (p, r, and q) can range between zero and one, where zero is no decay and one is total decay.

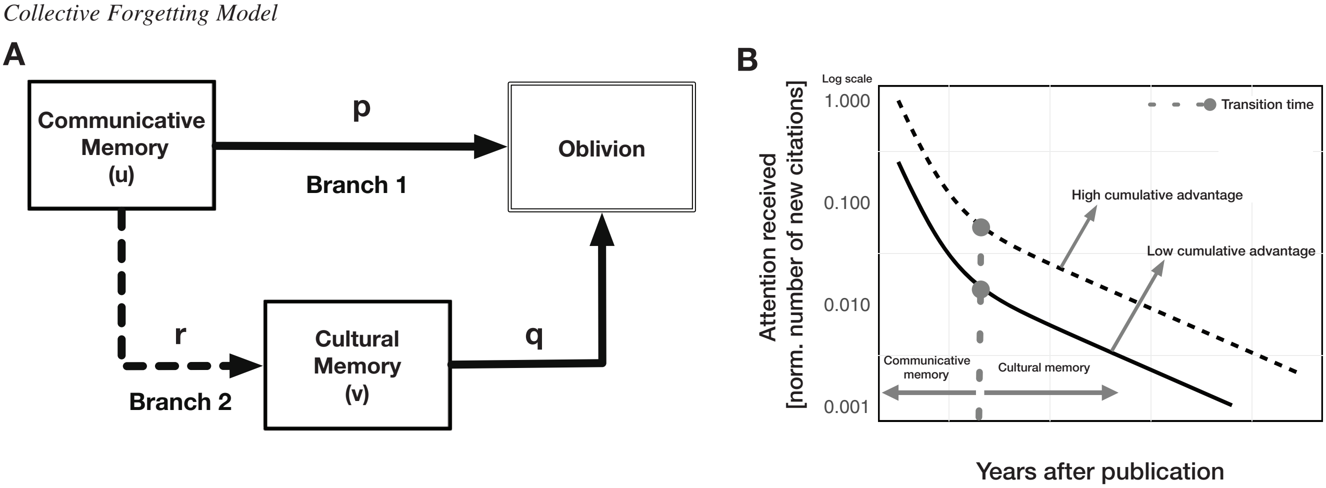
The model's inclusion criterion requires comparable cultural pieces, for example, same age and similar levels of accumulated citations. Figure 1B shows an example of cultural pieces with the same age but two different levels of cumulative advantage: high (dashed line Figure 1B) and low (solid line Figure 1B; see Appendix B for more details). The model exhibits a transition time (gray dots Figure 1B) composed of two different states. At first, communicative memory is the most important attention source because it starts feeding cultural memory immediately. Next, cultural memory overcomes communicative memory, becoming the most important attention source (Figure 1B). This two-step forgetting model enables us to explore further the dynamics of forgetting (for more details about the model, see Appendix C).

Qualitatively, the model expresses the following relationships. Let us consider a set of comparable cultural pieces, C (same cohort Figure B1A and the same accumulated number of citations, Figure B1B). If we increase the rate at which communicative memory feeds cultural memory, r, the communicative memory decays faster (Figure B1C). However, more cultural pieces decay to oblivion through the cultural memory path that has a higher level of attention (Figure D1B, dashed line). Thus, an increase in r results in a slower forgetting for the set of cultural pieces, C, due to a cultural memory's attention premium. By increasing p (Figure D1C), the communicative memory decays faster to oblivion, making the entire system decay attention faster. Finally, increasing the decay rate of cultural memory q does not cause changes in communicative memory decay. Still, the entire system forgets faster (Figure D1D, dashed line) given the faster decay of cultural memory (for more details about the model relationships, see Appendix D).

To summarize all the model variables (p, q, and r), we define the attention decay rate of scientific articles and patents, i.e., the probability of transitioning from communicative memory to oblivion, as $\lambda = q(p + r)/(q + r$; see Appendix E for the mathematical derivation). Higher forgetting rates indicate higher attention loss each time. In our case, the forgetting rate spans from .1 to .6 (approximately), where, for instance, a forgetting rate of .6 indicates that collective attention decays 60% in each year after publication.

Given that the model allows two paths to oblivion, it is possible to define the share of cultural products that follow each forgetting branch (Figure 1A), i.e., those going to oblivion directly ($B_1 = p/(p + r)$) or through cultural memory ($B_2 = r/(p + r)$). For instance, if $p = 0$, all cultural products

Figure 1
Collective Forgetting Model



Note. (A) Communicative and cultural memory are transient states of the model, while oblivion is an absorbing state (double stroke box). Branches 1 and 2 are the paths to oblivion whose decay probabilities are $B_1 = p/(p + r)$ and $B_2 = q/(p + r)$, respectively. (B) Temporal decay of collective memory occurs after accounting for cumulative advantage (vertical curves). These two stages are distinguished before and after the transition time (vertical segmented line, 9 years). The first stage is dominated by communicative memory (to the left of the vertical segmented line). The second stage is dominated by cultural memory (to the right of the vertical segmented line).

follow the branch through cultural memory, B_2; or if $r = 0$, all cultural products follow the branch directly to oblivion (B_1).

Data Description

We use time-series data from patents and scientific articles to investigate the forgetting dynamics of inventors' and physicists' communities. For patents, we use the USPTO corpus. It contains data on $n = 1, 681, 690$ patents granted in the United States (see Appendix A for a patent example) from 1973 to 2005. The data are classified according to six different categories: Chemical (CAT 1), Computers and Computation (CAT 2), Drugs and Medical (CAT 3), Electrical and Electronic (CAT 4), Mechanical (CAT 5), and Others (CAT 6). We use data covering patents granted only from 1976 to 1995 and in all categories except Drugs and Medical. These USPTO restrictions are based on two considerations: (a) Drugs and Medical patents are missing entries from 1990 to 1995 and (b) five or more years are needed to follow patents' and papers' citations into the future after the transition time (t_c) to estimate reliable parameters for the forgetting model.[1]

For scientific articles, we use the corpus of articles published and archived by the APS. The corpus contains data about $n = 485, 105$ physics articles from 12 different journals, between 1896 and 2016.[2] We analyzed articles published in the Physical Review Series II (PR) from 1950–1969; four Physical Review Journals (PRA, PRB, PRC, and PRD) from 1970 to 1999; the Physical Review E (PRE) from 1993 to 1999; and the Physical Review Letters journal (PRL) from 1958 to 1999. Both data sets have been previously validated and studied in the literature (Candia et al., 2019; Higham et al., 2017a, 2017b; Jaffe et al., 1993; Shen & Barabasi, 2014; Sinatra et al., 2016; Wang et al., 2013).

Procedure

We implement a prospective approach (see Appendix B for more details; Bouabid, 2011; Glänzel, 2004; Yin & Wang, 2017) that focuses on following the memory processes of cohorts of cultural production (e.g., all papers published in PRA in 1990) to acquire new citations over time. We use the prospective approach because there is no mathematical difference with the retrospective approach (Yin & Wang, 2017) and because it is easier to implement (Bouabid, 2011; Glänzel, 2004).

Next, we build two time series for each patent and paper analyzed (see Figure B1B). The first comprises the new number of accrued citations, which is the number of citations obtained within a 1-year time window for each cultural product. The second contains the accumulated citations obtained up to a given time, which allows us to control for the cumulative advantage or popularity of cultural products (Candia et al., 2019; Higham et al., 2017a, 2017b). Indeed, to account for cumulative advantage effects and reveal the temporal pattern of collective forgetting for each cohort, we group all papers and patents in logarithmic buckets of accumulated citations. Thus, we build a time series for each cohort of cultural pieces in each group of accumulated citations (Figure 1B and Figure B1C).

We estimate the features of the collective memory and attention model (p, q, and r) for each community and year, and we average them across the different accumulated citation groups (see Appendix F for more details). For each model's variable, we build a structured panel dataset using categories (USPTO) or journals (APS) as grouping indexes and the cohort's year as the temporal index. Using this model's features, we build the forgetting rate (λ, see the mathematical derivation in Appendix E, and the temporal evolution of model variables in Appendix G) for each community and year.

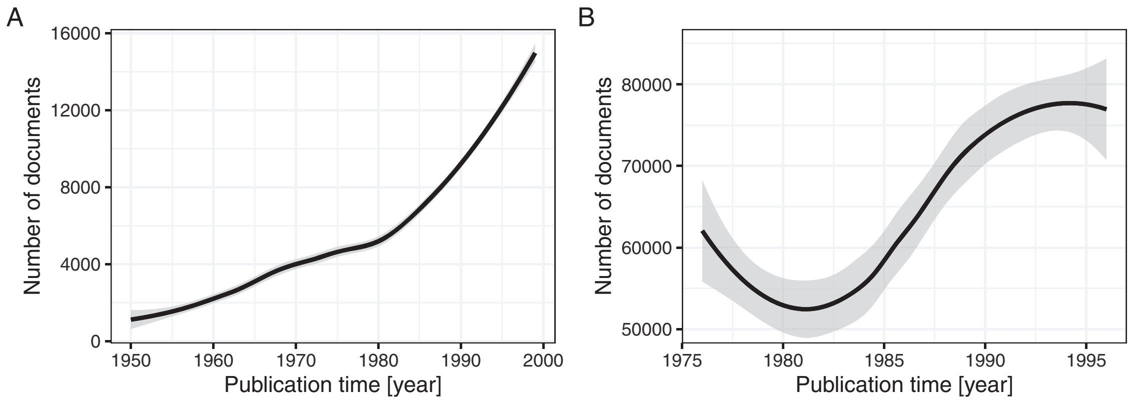
We test the hypothesis of forgetting as annulment on physicist and innovator communities by estimating different statistical models (pooled, within one-way, within two-ways, and first differences models, see Appendix H). We implemented the Driscoll and Kraay (1998) method for robust errors, which accounts for heteroskedasticity, autocorrelation, and cross-sectional dependence of the errors. We plot the number of APS scientific articles and the number of USPTO patents and observe that they follow an increasing trend Figure 2A and 2B).

To compare important and less important cultural pieces, we define two groups of documents for each community: (a) All documents with more than zero citations, which includes all documents published and granted of each cohort that have accrued at least one citation and, (b) the most-cited documents which include the top 15% of each cohort's most cited documents between $t_c \pm 1$ years after release. In other words, the top-cited groups are the most cited patents ($t_c = 5$) between the fourth and the sixth year after documents are granted and the most-cited papers ($t_c = 9$) between the eighth and 10th year after publication. We note that the top-cited documents include all the citation ties, i.e., if there is more than one document in the 15% bottom limit, we include all these documents in the group such as, for example, patents from 1990 in the "Mechanical" category (descriptive statistics for the number of citations in Table 1). Given that transition time is $t_c = 5$, we create the top-cited group of the 15% of papers that have accrued the highest number of citations between 1994 and 1996 (i.e., 5 ± 1 years). In this case, although we fix the top-cited group as the top 15% of

[1] The transition time is defined as the time at which cultural memory overcomes communicative memory (Candia et al., 2019), that is for papers $t_c \approx 9$ years and for patents and $t_c \approx 5$ years.

[2] Some of these journals do not exist anymore, some others are too small in terms of the number of publications, and one of them only publishes reviews, which follow a completely different citation dynamic.

Figure 2
Number of Documents Over Time



Note. Total number of published papers (A) and total number of granted patents (B) in all categories for each year. Lines are the moving average, and the gray shadows are the 95% confidence intervals.

patents, there are several ties, leading to a final 35.9% of documents in the group (4,186 out of 11,640).

Results

To investigate how physicist and innovator communities forget over time, we compute the decay-rate variables p, q, and r. We observe an increasing trend for all the decay rates (except for patents after the 90s; Figure 3A–B and Figure G1), implying attention increases as r increases, and attention declines as p and q increase (Figure D1 from B to D).

To have a clearer picture of the attention decay for an entire community each year, we compute the forgetting rate, λ, as the probability of transitioning from communicative memory to oblivion, where higher values indicate quicker forgetting. For the APS community (Figure 3C), we observe an accelerating forgetting for both top-cited papers (dashed line) and all papers considered as a whole (solid line). In the USPTO community (Figure 3D), we observe an oscillating forgetting trend for all patents (solid line) and a decreasing forgetting rate for top-cited patents (dashed line). Central to this study, within each community, we observe a similar trend between the forgetting rate (Figure 3C and 3D) and the number of cultural productions (Figure 2A and 2B). This relationship is in line with theoretical literature that suggests a positive relationship between the increasing amounts of information and forgetting rates, i.e., forgetting as annulment (Connerton, 2008).

The forgetting as annulment hypothesis is tested for both APS (see Table 2) and USPTO (see Table 3) communities and their subcommunities with each table representing the knowledge field of journals and categories, respectively. A significant and positive effect is observed for each specification in each community, providing evidence that excess information induces forgetting. The effect survives above and beyond subcommunities (represented by the entities' fixed effects in Models 3 and 4 in Tables 2 and 3) and time (represented by both entities' fixed effects and temporal fixed effects in Models 5 and 6 in Tables 2 and 3). Concretely, an increase of 10,000 APS papers (Model 6 Table 2) leads to an increase in the forgetting rate of 16.8%. Additionally, an increase of 10,000 USPTO patents (Model 6 Table 3) leads to an increase in the forgetting rate of 10.6%.

Moreover, given that some of the specification could exhibit serial correlation in the errors (u_{it}), we report the

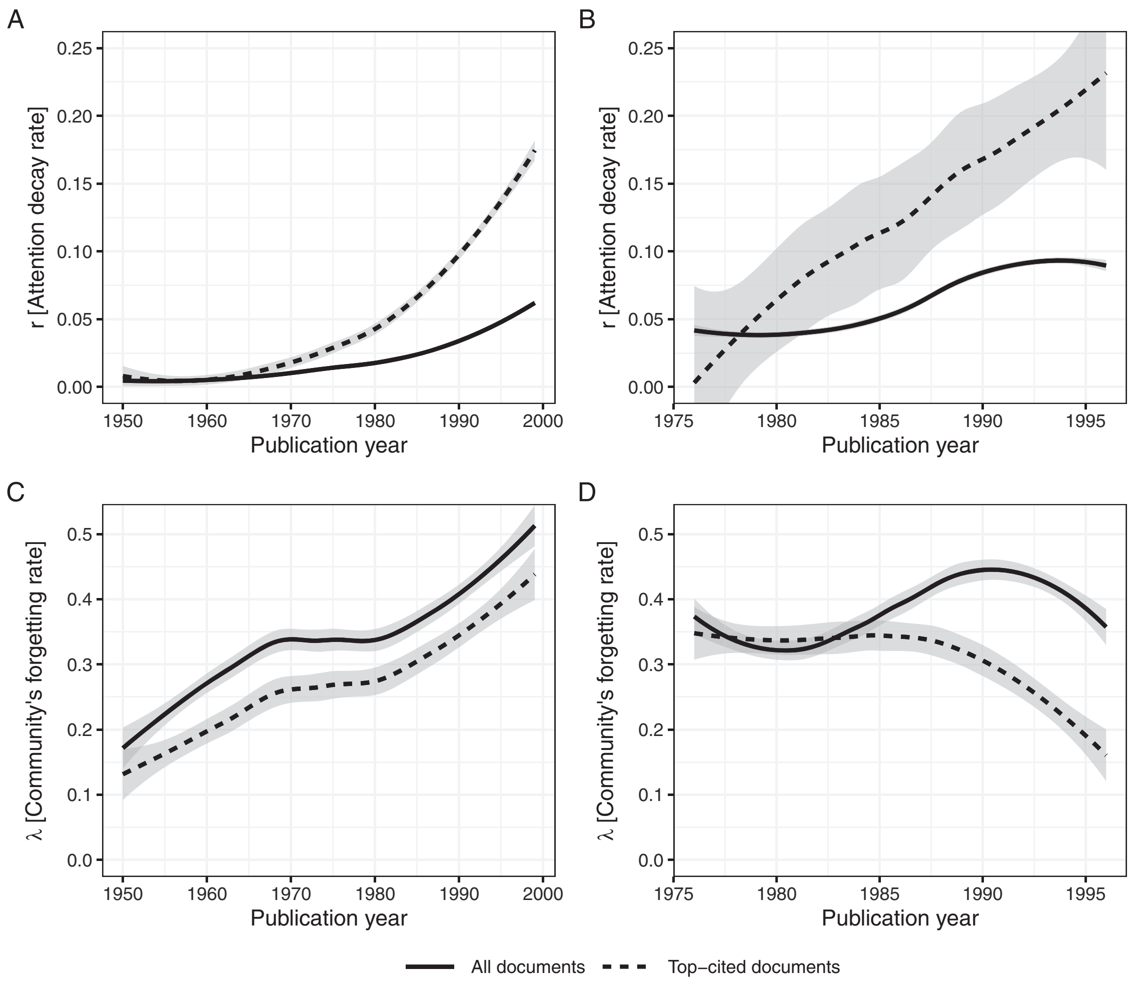
Table 1
Descriptive Statistics of Mechanical Patents Granted in 1990 for the Number of Citations

Descriptive statistic	All (N = 11,640)	Others (N = 7,454)	Top cited (N = 4,186)
Min	1	1	3
Mean (*SD*)	11.65 ± 12.77	7.59 ± 6.26	18.88 ± 17.38
Median (IQR)	8.00 (5.00, 14.00)	6.00 (4.00, 10.00)	14.00 (9.00, 22.00)
Max	265	129	265

Note. The first column is for all patents, the second column is for the 15% top-cited patents, and the third column is for the other 85% of patents. The top-cited documents include all the ties, which means that some groups can be bigger than the 15%. Note that documents with zero accumulated citations (7,401 patents in the mechanical category) are not considered for calculate model's variables.

Figure 3

Forgetting Rates for APS (Left Column) and USPTO Communities (Right Column)



Note. Solid lines represent all aggregated documents, and dashed lines represent the top-cited 15% of documents after t_c years. (A) and (B) are attention decay rates from communicative memory to cultural memory (r, coupling rate, i.e., the interaction variable). The community forgetting rates (λ) for the American Physical Society (APS) community are (C) and, for the United States Patent and Trademark Office (USPTO) community, (D).

coefficients using robust standard errors (Driscoll & Kraay, 1998) for each specification (Models 2, 4, and 6 in Tables 2 and 3) that also confirms the forgetting as annulment hypothesis. We observe no serial correlation in the difference of the errors (Δu_{it}), and a first difference estimator is computed (Models 7 in Tables 2 and 3). This model also includes a lag for the number of documents and a lag for the forgetting rate. The first difference estimator also supports the forgetting as annulment hypothesis in both communities.

Finally, we run a Levin-Lin-Chu test for stationarity (Levin et al., 2002), which computes an augmented Dickey-Fuller (ADF) for each time series. The test specifies a term for each individual intercept and a term for each trend in the ADF regressions. If both intercept and trend are zero, the time-series is well described by a random walk. If only the trend is zero, that corresponds to a random walk with a vertical displacement. Finally, lagged terms are included. The test's rationale is that the lagged level of the time series will provide no meaningful information if a unit root is present (null hypothesis). We find that the test rejects the null hypothesis (nonstationary time series) with a p-value $< .05$ for both variables forgetting rate and the number of documents in both data sets (except for the number of papers; p-value = .19). Then, we run the same test for the first differences, and all variables reject the null hypothesis, indicating stationarity in the time series. Thus, our results provide robust evidence that an excess of information promotes forgetting in knowledge communities.

Can communities weaken the annulment process by focusing more attention on important cultural productions? After

Table 2
Regression Models for APS Papers

	Dependent variable						
	Forgetting rate						Forgetting rate (log)
Explanatory variable	Panel linear (1)	Coefficient test (2)	Panel linear (3)	Coefficient test (4)	Panel linear (5)	Coefficient test (6)	Panel linear (7)
N papers	2.60*** (0.29)	2.60*** (0.37)	3.75*** (0.29)	3.75*** (0.47)	0.84** (0.38)	0.84*** (0.29)	
N papers (log)							0.30** (0.12)
Lag *N* papers (log)							0.12 (0.11)
Lag forgetting rate (log)							–0.48*** (0.07)
Constant	0.29*** (0.01)	0.29*** (0.01)					
Effect	Pooling	SCC	Within one-way	SCC	Within two-ways	SCC	First differences
R^2	0.32		0.7		0.82		0.24
Adjusted R^2	0.32		0.69		0.74		0.23
Observations	189		189		189		175
F statistic	79.91*** ($df = 1; 187$)		173.07*** ($df = 1; 181$)		4.83** ($df = 1; 132$)		18.37*** ($df = 3; 172$)

Note. APS = American Physical Society. Note that the number of papers is scaled by 50,000 and for first differences we consider the logarithm of the data. SCC: Driscoll and Kraay's (1998) method. Robust errors for heteroskedasticity, autocorrelation, and cross-sectional dependence.
** $p < .05$. *** $p < .01$.

all, the forgetting rate, λ, is always lower for top-cited cultural pieces (dashed lines in Figure 4A and 4B) than it is when all cultural pieces are compared regardless of citation levels (solid lines in Figure 4A and 4B).[3] Which mechanism drives the observed smaller forgetting rate? The decay rates of communicative memory (p) and cultural memory (q) are statistically equivalent for both groups of documents (Figure 3A, 3B, 3C, and 3D). This equivalence suggests that the communities cannot (or at least not easily) manipulate these rates. Hence, the differences in the forgetting rate (λ) between the two groups are due to the coupling rate r, which corresponds to the magnitude of the interaction between communicative and cultural memory. Indeed, the APS and USPTO communities increase their coupling rates faster for top-cited cultural pieces (dashed line Figure 3A and 3B) when compared with all produced cultural pieces (solid line Figure 3A and 3B).

Thus, because of the differences in the coupling parameter r, the share of scientific articles and patents that decay directly to oblivion (i.e., Branch 1, $B_1 = p/(p + r)$) is also smaller for top-cited cultural pieces (dashed lines in Figure 4A and 4B) than for all produced cultural pieces (solid lines in Figure 4A and 4B). Similarly, the share of scientific articles and patents that decay from communicative memory to cultural memory (i.e., Branch 2, $B_2 = r/(p + r)$) is bigger for top-cited cultural pieces than for all produced cultural pieces. For instance, the 85% of all USPTO patents granted in 1995 went directly to oblivion, while 75% of the top-cited papers went directly to oblivion. We show that communities increase their coupling rate faster when it comes to important cultural pieces (top-cited documents), which means that communities react to forgetting as annulment by increasing their selectivity.

Discussion

Herbert Simon (1971) wrote, "A wealth of information creates a poverty of attention and a need to allocate that attention efficiently among the overabundance of information sources that might consume." Simon's work has for decades inspired scholars studying attention economics (Davenport & Beck, 2001; Lanham, 2006; Weng et al., 2012). Yet, little is known about the mechanisms that drive collective attention's temporal changes or how communities react to those changes.

Here, we tackle one of the factors that impact collective attention through the lens of collective memory psychology, and it can be summarized as follows: The excess of information promotes forgetting in knowledge communities, namely technological (inventor) and academic (physicist) communities. This effect was theoretically described by Connerton (2008) under the name of forgetting as annulment. The data analysis supports this hypothesis (Tables 2 and 3). We provide, for each community, empirical evidence of the positive relationship between the amount of information produced (number of published or granted documents) and the forgetting rate, which is calculated using a collective attention model fully grounded on collective memory literature (Candia et al., 2019).

[3] Defined as the top 15% of the most cited documents between $t = t_c \pm 1$ years after release.

Table 3
Regression Models for USPTO Patents

Explanatory variable	Forgetting rate: Panel linear (1)	Forgetting rate: Coefficient test (2)	Forgetting rate: Panel linear (3)	Forgetting rate: Coefficient test (4)	Forgetting rate: Panel linear (5)	Forgetting rate: Coefficient test (6)	Forgetting rate (log): Panel linear (7)
N papers	1.19*** (0.17)	1.19*** (0.10)	1.30*** (0.17)	1.30*** (0.18)	1.06** (0.40)	1.06*** (0.06)	
N papers (log)							–0.11 (0.12)
Lag *N* papers (log)							0.23** (0.11)
Lag forgetting rate (log)							–0.05 (0.12)
Constant	0.19*** (0.03)	0.19*** (0.03)					
Effect	Pooling	SCC	Within one-way	SCC	Within two-ways	SCC	First differences
R^2	0.38		0.47		0.75		0.11
Adjusted R^2	0.38		0.45		0.65		0.09
Observations	80		80		80		72
F statistic	50.25*** (df = 1; 78)		55.57*** (df = 1; 75)		6.98** (df = 1; 56)		2.84** (df = 3; 69)

Note. USPTO = United States Patent and Trademark Office. The number of papers is scaled by 100,000 and for first differences we consider the logarithm of the data. SCC: Driscoll and Kraay's (1998) method. Robust errors for heteroskedasticity, autocorrelation, and cross-sectional dependence.
** $p < .05$. *** $p < .01$.

Forgetting as annulment becomes an important issue when a community's capacity to remember what is worth remembering is affected, modulating the community's cultural evolution. A high number of cultural products and their easy archivalization create the perfect scenario to forget valuable cultural pieces. In the information era, characterized by vast amounts of data, understanding the filtering problem is central to preserving and building knowledge. Indeed, Kuhn (1970) suggests that paradigm shifts happen when new knowledge overcomes and overtakes existing knowledge. With an increasing knowledge production rate, knowledge communities must adjust their filtering capacities to keep track of what information is worth remembering and what is not. For example, recent research shows that people who belong to multiple groups can accelerate cumulative cultural evolution (Migliano et al., 2020), fostering selective remembering. On the other hand, not recording information can lead to the loss of valuable technologies such as the case with the bone tools in Tasmania (Henrich, 2004) and the case with the canoes' construction at Torres Island in Oceania (Rivers & Smith, 1926).

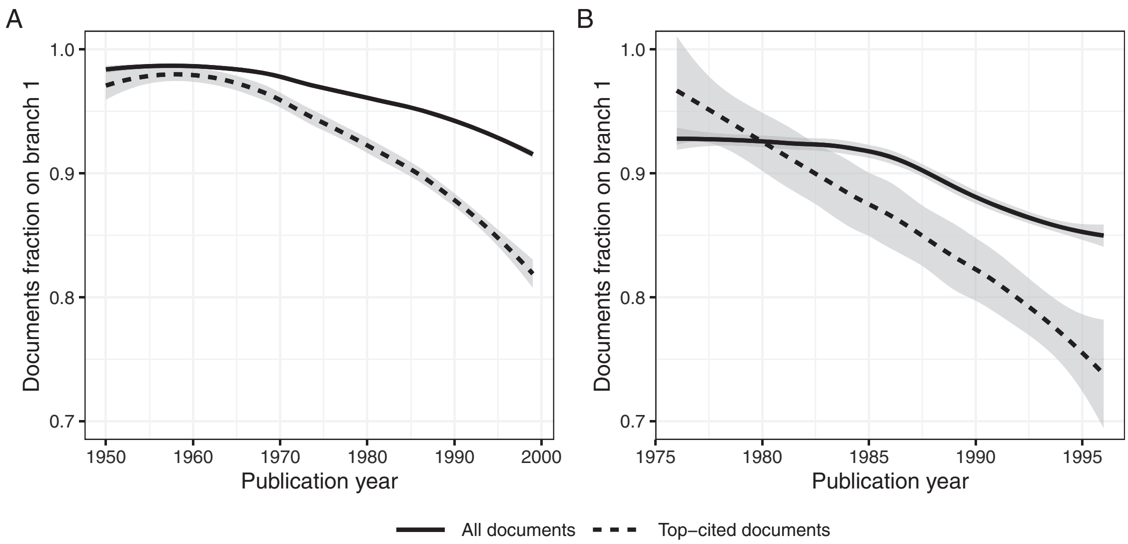
Storing valuable content in the cultural memory is another potential mechanism for slowing down the increase in forgetting rates. We can reasonably argue that filtering capacities are more efficient in communities where cultural products' production depends on objective processes (science and invention) than subjective processes (music, movies, and arts). The data analysis shows that communities of inventors' and physicists' increase their coupling rate (r) for top-cited documents (Figure 3A and 3B). The coupling rate differences between all documents and the top-cited documents suggest that both knowledge communities respond to the increasing forgetting. They actively select pieces of information worth remembering and store them in their cultural memory (Figure 4), where they live longer in a mode of actuality (Assmann, 1995).

Data science methods help us measure the dynamical aspects of the cultural evolution of communities. We operationalize collective memory and attention using Assmann's definition as the collection of cultural expressions that a group of people remembers (i.e., remembering acts). This process includes using data on online attention to quantifying memory at a population scale, allowing us to distinguish communicative and cultural memories using a mathematical model. Thus, we leverage data on millions of papers and patent citations, capturing the cultural context of inventors' and physicists' communities for each year to understand better how inventors and physicists impact the way they forget over time. This approach's benefits rely on quantifying the driving forces of collective memory and attention, making it possible to use these patterns and models as starting points for individual-level studies.

Indeed, these results provide insights into the temporality of collective memory and attention, which could have potential real-world consequences ranging from performance in sports (Yucesoy & Barabási, 2016), arts (Fraiberger et al., 2018), and science (Candia et al., 2019; Higham et al., 2017a; Wang et al., 2013) to the resilience of a country experiencing trauma (Mehl & Pennebaker, 2003) or for developing efficient communication strategies

Figure 4

Branch Fraction for American Physical Society (APS; Left Column) and United States Patent and Trademark Office USPTO Communities (Right Column)



Note. Solid lines represent all aggregated documents, and dashed lines represent the top-cited 15% of documents after t_c years. (A and B) display the fraction of documents decaying through Branch 1 (i.e., the share of directly forgotten documents). Note that the complement share of documents decay through Branch 2 (i.e., the share of documents going to cultural memory).

to improve policy awareness (Cunico et al., 2021). To understand the communicative and cultural memory mechanisms of collective forgetting in other domains, Coman (2019) provides a brilliant example. Days after the September 11th attacks, New Yorkers gathered together in small groups of close friends to debate the events and share their experiences (Mehl & Pennebaker, 2003). They communicated with each other as the easiest way to share information and to deal with the trauma. In the months and years after the immediate consequences of the September 11th events, newspaper articles, makeshift memorials, books on the subject, and official commemorations served as recurrent reminders of the tragedy. Both the communicative acts occurring right after the attacks (i.e., communicative memories) and the physical artifacts that served as reminders of the attacks (i.e., cultural memories) have shaped the collective memories of New Yorkers and all Americans. In other words, as in the case of that specific attack, events catch the attention of small groups of people, who may pass it on to others. Therefore, a positive-reinforcement effect sets in that the more popular the story becomes, the faster it spreads.

Limitations and Future Directions

We use citations between documents as a proxy to measure collective memory and attention, which is in line with Assmann's definition of collective memory: the collection of cultural expression that a group of people remembers. This definition justifies the use of papers and patents citations as acts of remembering. Yet, a limitation of the analysis is that different forms of memory or attention loss such as interference, suppression, inhibition, or structural amnesia (Barnes, 1947) are averaged together.

In the model, attention results from retrieving information from our collective memory, either communicative or cultural memory. The interacting variable (r) is a simplified parameter attempting to capture a very complex process that needs to be studied in depth. However, using this stylized model enable us to explore the leading forces governing the temporal dimension of collective memory and attention decay, which cannot be neglected when modeling collective memory systems.

Future work could explore whether different forms of memory or attention loss (suppression, inhibition, among others) have similar or different dynamics. Besides, the inclusion of second-order effects for the interacting variable could provide more detailed insights, particularly for study cases. On the same token, explore particular dynamics within knowledge communities could provide helpful information for decision-makers. For instance, in academic departments where research topics are forgotten fast, it might be beneficial to modify the time funding for postdocs and grants accordingly.

Our computational social science approach to the study of collective memory and attention can complement studies from the literature on cognitive psychology and cultural evolution.

For instance, it would be possible to mathematically separate different forgetting mechanisms that in our current approach are averaged together by using agent-based models grounded on the cultural evolution literature. Isolating the rules that lead to the aggregated temporal patterns of collective memory and attention would significantly contribute to understanding the primary individual-level mechanism that modulates collective forgetting.

Finally, our present and future are modulated by increasing amounts of data produced daily in traditional and automatized processes by different groups of people. This fact raises several known challenges: integrating, distributing, analyzing, and visualizing such large amounts of data. Here, we vindicate a new challenge: society's information filtering capacities. We have shown that filtering capacities have been increasing for scholars and inventors. Indeed, they have done well at remembering essential pieces of knowledge for their communities. However, what about the rest of our society? Are we ready to face the challenge of not forgetting helpful information, ideas, and techniques? or will we repeat the same as with bone tools in Tasmania and the canoes' construction in Torres Island? Future directions should focus on studying other cultural domains. Extending the analysis to other cultural domains (e.g., music, performing arts, or online blogs) will provide empirical evidence, whether on the universality or the heterogeneity of the forgetting as annulment for different cultural domains, as well as a detailed description of the life-cycles of cultural pieces, knowledge, and information.

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Appendix A

Patent Example

A patent is a limited duration property right relating to an invention and granted by the United States Patent and Trademark Office (USPTO) in exchange for public disclosure of the invention.[A1] Figure A1A shows the first two pages of the" Rotary Cutting Assembly" patent, in which we observe identification information including the inventors' names, the application number, filing date, information on related previous applications, cited references, and the abstract.[A2] The patent also includes schematic representations of the invention and a detailed description of it.

The patenting process typically lasts around 2 years, and citations to patents can be achieved in two different manners. First, patent applicants are required to provide a list of the most relevant previous inventions. Then examiners (people who study if the submitted invention is patentable or not) evaluate the citation list, and they can delete irrelevant citations. Second, the examiner provides a list of other relevant references, usually after the examination process. Sometimes, these new references leads to the rejection of the invention's patent depending on the level of innovation overlap. Figure A1B shows the last citations to the "Rotary Cutting Assembly." We observe that the citations made by examiners are marked with an asterisk.

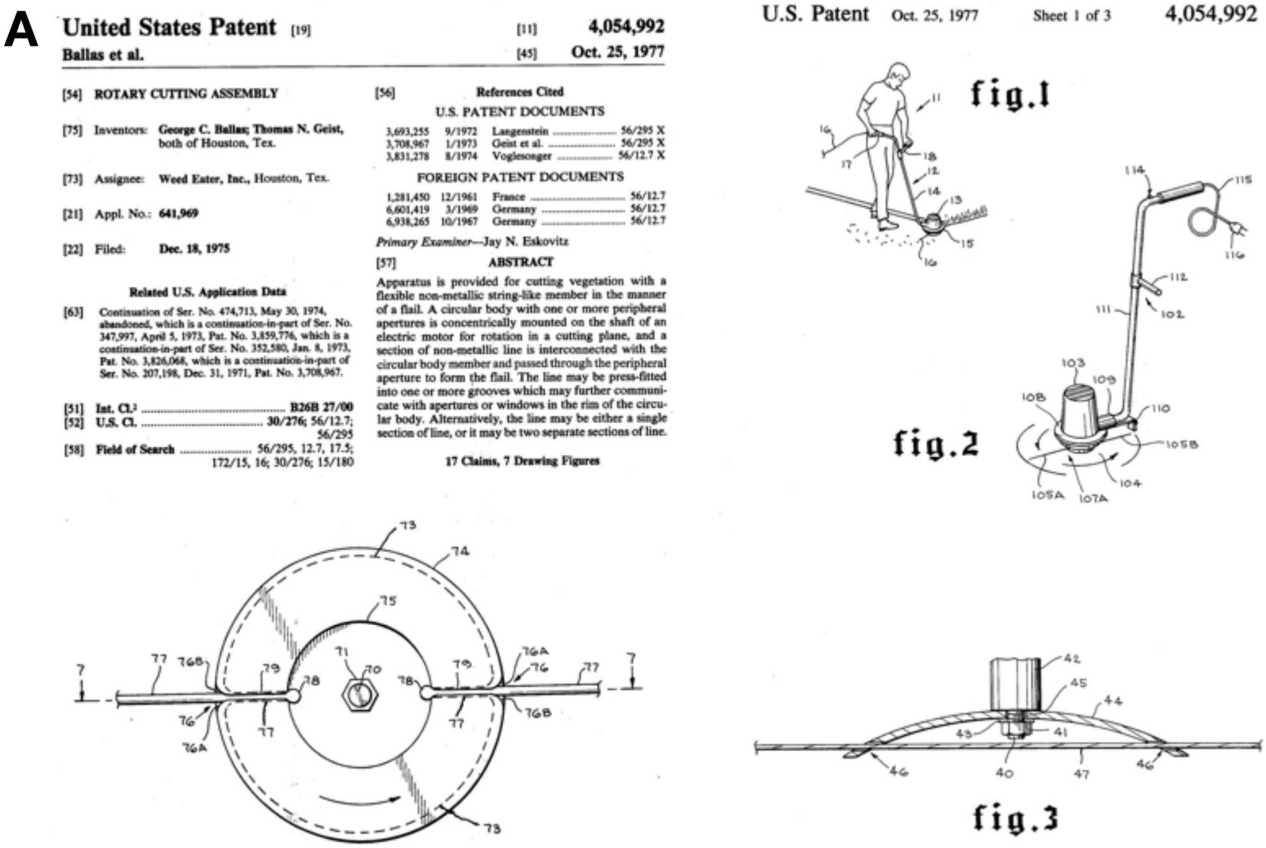
[A1] https://www.uspto.gov.

[A2] https://patents.google.com/patent/US4054992.

(*Appendices continue*)

Figure A1
Patent Example

A


United States Patent [19]
Ballas et al.

[11] 4,054,992
[45] Oct. 25, 1977

[54] ROTARY CUTTING ASSEMBLY

[75] Inventors: George C. Ballas; Thomas N. Geist, both of Houston, Tex.

[73] Assignee: Weed Eater, Inc., Houston, Tex.

[21] Appl. No.: 641,969

[22] Filed: Dec. 18, 1975

Related U.S. Application Data

[63] Continuation of Ser. No. 474,713, May 30, 1974, abandoned, which is a continuation-in-part of Ser. No. 347,997, April 5, 1973, Pat. No. 3,859,776, which is a continuation-in-part of Ser. No. 352,580, Jan. 8, 1973, Pat. No. 3,826,068, which is a continuation-in-part of Ser. No. 207,198, Dec. 31, 1971, Pat. No. 3,708,967.

[51] Int. Cl.² B26B 27/00
[52] U.S. Cl. 30/276; 56/12.7; 56/295
[58] Field of Search 56/295, 12.7, 17.5; 172/15, 16; 30/276; 15/180

[56] References Cited

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3,831,278	8/1974	Voglesonger	56/12.7 X

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Primary Examiner—Jay N. Eskovitz

[57] ABSTRACT

Apparatus is provided for cutting vegetation with a flexible non-metallic string-like member in the manner of a flail. A circular body with one or more peripheral apertures is concentrically mounted on the shaft of an electric motor for rotation in a cutting plane, and a section of non-metallic line is interconnected with the circular body member and passed through the peripheral aperture to form the flail. The line may be press-fitted into one or more grooves which may further communicate with apertures or windows in the rim of the circular body. Alternatively, the line may be either a single section of line, or it may be two separate sections of line.

17 Claims, 7 Drawing Figures

B

Cited By (67)

Publication number	Priority date	Publication date	Assignee	Title
US20090100686A1 *	2007-10-22	2009-04-23	Mtd Products Inc	Fixed-line rotary head for string trimmer machine
US20090114738A1 *	2006-04-14	2009-05-07	Barbara Annese	Self-moved device for colouring or spraying a surface
US20100101099A1 *	2008-10-28	2010-04-29	Morabit Vincent D	Line Loader for a Grass Trimmer
US20100154228A1 *	2008-12-20	2010-06-24	Watts David L	Non-spooled trimmer line
US20130247386A1 *	2010-12-06	2013-09-26	Taisemonac Co., Ltd.	Shoulder-Hanging Type Grass Cutter
US20130312322A1 *	2010-09-10	2013-11-28	Juan Antonio Sagarra Dolset	Device for Thinning and Harvesting Fruit and Flowers
US9027479B2	2002-07-15	2015-05-12	Jds Uniphase Corporation	Method and apparatus for orienting magnetic flakes
USD757508S1 *	2014-08-12	2016-05-31	Martin Hermann	Square trimmer line
USD759444S1 *	2014-08-12	2016-06-21	Martin Hermann	Circular trimmer line
US10064329B1 *	2011-04-14	2018-09-04	August Otto Lovmark	Trimmer head with anti-fouling mechanism
US10232660B2	2012-01-12	2019-03-19	Viavi Solutions Inc.	Article with curved patterns formed of aligned pigment flakes
US10273112B2	2006-11-16	2019-04-30	Torvian Inc.	String trimmer head with curved trimmer line guide
Family To Family Citations				

* Cited by examiner,

Note. (A) The two first pages of the Rotary Cutting Assembly patent, granted in 1975. (B) The lasts citations received by this patent. Asterisks show the citations made by examiners.

(*Appendices continue*)

Appendix B

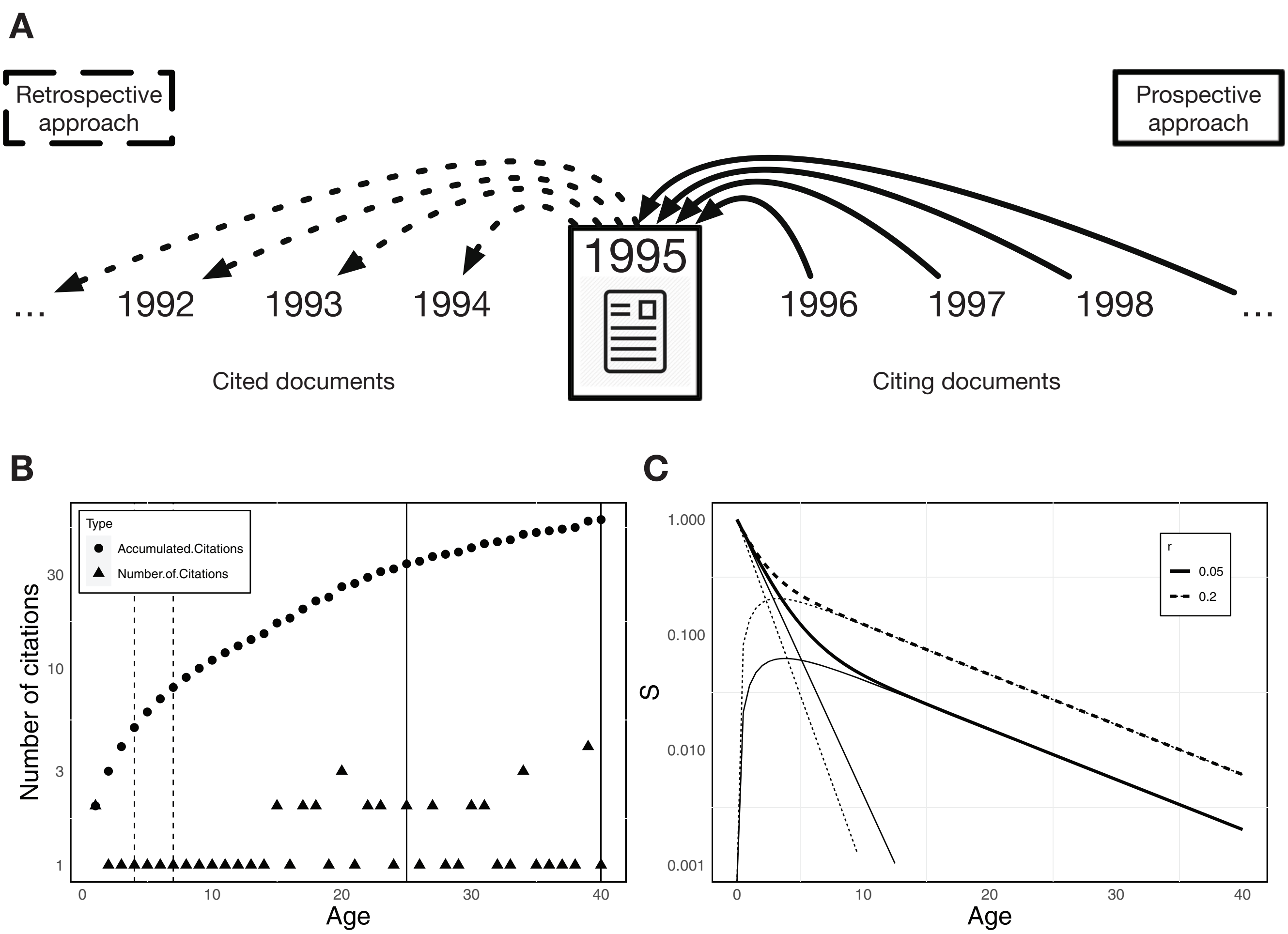
Tracking Future Citations

In the retrospective approach (dashed arrows, Figure B1A), the focus is to track the cited documents of each specific cohort (looking at the past). In the prospective approach (solid arrows, Figure B1A) the focus is on tracking the citing documents of each specific cohort (looking at the future). We focus on the prospective approach.

Figure B1B shows both time series used in our model. Triangles represent the number of accrued citations in a time window of 1 year. Circles represent the number of accumulated citations over time. We group comparable cultural pieces by considering the same cohort and a log-binning in the accumulated citations time series. For instance, in a specific cohort, we group separately all papers with between 33 and 66 accumulated citations and all the papers with between four and eighth accumulated citations separately. Therefore, the paper represented in Figure B1B is grouped under the former category after 25 years of first publication (between vertical solid lines) and is grouped in the latter category between its fourth and seventh year after publishing (between vertical dashed lines).

In Figure B1C, the thin lines represent the collective memory decay's decomposition in its two components: communicative memory (straight lines) and cultural memory (peaked curves). For higher values of r (e.g., $r = .2$, dashed lines), the communicative memory (straight-dashed line) decays faster than lower r (e.g., $r = .05$, straight-solid line). However, the cultural memory is fed with a higher rate, resulting in an attention premium for the entire system (the thick straight line is above the thick solid line).

Figure B1
Tracking Collective Attention



Note. (A) Scheme for the retrospective and prospective approach for tracking citations. (B) Time series building example to account for cumulative advantage. (C) Decomposition of the feed rate (r) in its communicative and cultural memory parts.

(*Appendices continue*)

Appendix C

Model

We model the collective attention received by cultural pieces by assuming that the collective attention size occupied by comparable cultural pieces for all *time t* is $S(t) = u(t) + v(t)$. S is the sum of the collective attention size on communicative memory (u) and cultural memory (v). We note that the decay of the collective attention size of a particular cultural piece is entirely random in time so it is impossible to predict when a particular cultural piece will be remembered. However, the collective attention size ($S(t)$) for a particular cultural piece is equally likely to decay at any instant in time. Therefore, given a set of comparable cultural pieces (discounted by preferential attachment and having the same age), the number of remembering acts $-dS$ expected to occur in a small interval of time dt is proportional to the size of collective attention S, that is $\frac{-dS}{dt} = \propto S \Rightarrow \frac{-dS}{S} = \propto dt$.

Thus, the expected decay of collective attention size, $-dS/S$, is proportional to an increment of time, dt, where the negative sign indicates that the collective attention size decreases as time increases. Considering that $S = u + v$, with initial conditions $u(0) = N$ and $v(0) = 0$, the solution of this coupled differential equation system (Candia et al., 2019) depicted in Figure 1 is:

$$u(t) = Ne^{-(p+r)t}, \quad v(t) = N\frac{r}{p+r-q}\left[e^{-qt} - e^{-(p+r)t}\right], \tag{1}$$

where N is the total size of collective attention at *time* $t = 0$, p is the decay rate from communicative memory to oblivion, q is the decay rate from cultural memory to oblivion, and r is the coupling rate between communicative and cultural memory, meaning the rate at which communities include cultural pieces in their cultural memory.

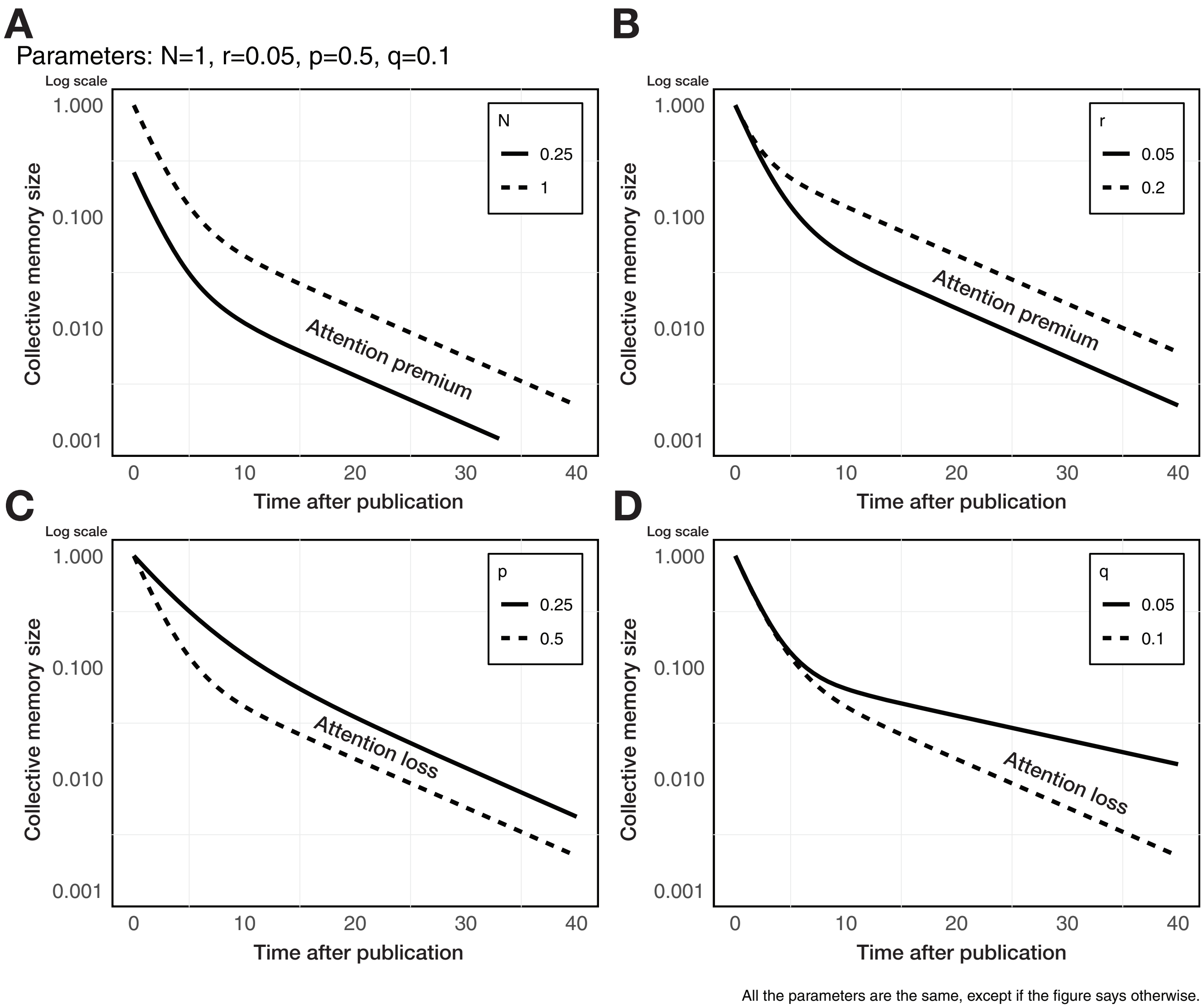
Appendix D

Model Features

Consider a set of comparable cultural pieces, C (same cohort Figure B1A and same accumulated number of citations, Figure B1B). An increase in the initial size of the collective memory (N) related to C, moves the forgetting curve up in the vertical direction (Figure D1A, dashed line). This results in an attention premium for the entire system for higher levels of initial popularity, represented by the area between the solid and the dashed line. If we increase the rate at which communicative memory feeds cultural memory (r), the communicative memory decays faster (Figure B1C). However, more cultural pieces decay to oblivion through the cultural memory path that has a higher level of attention (Figure D1B, dashed line). Thus, an increase in r results in a slower forgetting for the set of cultural pieces, C, due to the cultural memory's attention premium. By increasing p (Figure D1C), the communicative memory decays to oblivion faster, making the entire systems decaying its attention at a faster speed. This attention loss is represented by the area between the dashed and the solid line. It is worth noting that when the decay rate of communicative memory ($p + r$) is close to the decay rate of cultural memory (q), the decay of the system tends to a single exponential (straight line in a log-linear plot). Finally, increasing the decay rate of cultural memory (q) does not make changes in communicative memory decay; the entire system still forgets faster (Figure D1D, dashed line) because of the faster decay of cultural memory. The attention lost due to changes in the forgetting rate of cultural memory is represented by the area between the dashed and the solid curves in Figure D1D.

(*Appendices continue*)

Figure D1
Model Parameter Variations Induce Collective Attention Changes



Note. A graphical depiction of the attention loss and premium due to (A) the initial size of the collective memory (N) related to particular cultural pieces; (B) the rate at which communities include cultural pieces from communicative memory to cultural memory (r); and (C and D) the forgetting rates of communicative (p) and cultural memory (q).

Appendix E

Forgetting Rate

Let's consider a system with $t = 2$ transient states (communicative and cultural memory) and $a = 1$ absorbing state (oblivion), where the probability of transitioning from one transient state to another is given by Q, the probability of transitioning from a transient state to the absorbing state is given by R, and the canonical form of the transition matrix P of an absorbing Markov chain is given by P:

$$Q=\begin{bmatrix}1-r-p & r\\ 0 & 1-q\end{bmatrix}, R=\begin{bmatrix}p\\ q\end{bmatrix}, \text{ and } P=\begin{bmatrix}Q & R\\ 0 & I\end{bmatrix}=\begin{bmatrix}1-r-p & r & p\\ 0 & 1-q & q\\ 0 & 0 & 1\end{bmatrix}$$

Then, the fundamental matrix that quantifies the probability of visiting a certain transient state is given by N.

(*Appendices continue*)

$$N = (I - Q)^{-1} = \begin{bmatrix} r+p & -r \\ 0 & q \end{bmatrix}^{-1} = \frac{1}{q(r+p)} \begin{bmatrix} q & r \\ 0 & r+p \end{bmatrix}$$

The N matrix enable us to calculate different properties of a Markov chain. The focus here is the number of steps (time) before cultural productions are absorbed by the oblivion state starting from both transient states (communicative and cultural memory).

$$N \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \frac{1}{q(r+p)} \begin{bmatrix} r+q \\ r+p \end{bmatrix}$$

Given the assumption that all the collective attention starts at the communicative memory transient state, the number of steps before cultural productions starting at the communicative memory are absorbed by the oblivion state is given by the first component of the previous matrix, τ. The forgetting rate is defined as $\lambda = 1/\tau$.

$$\tau = \frac{1}{\lambda} = \frac{r+q}{q(r+p)}$$

$$\lambda = \frac{q(r+p)}{r+q}$$

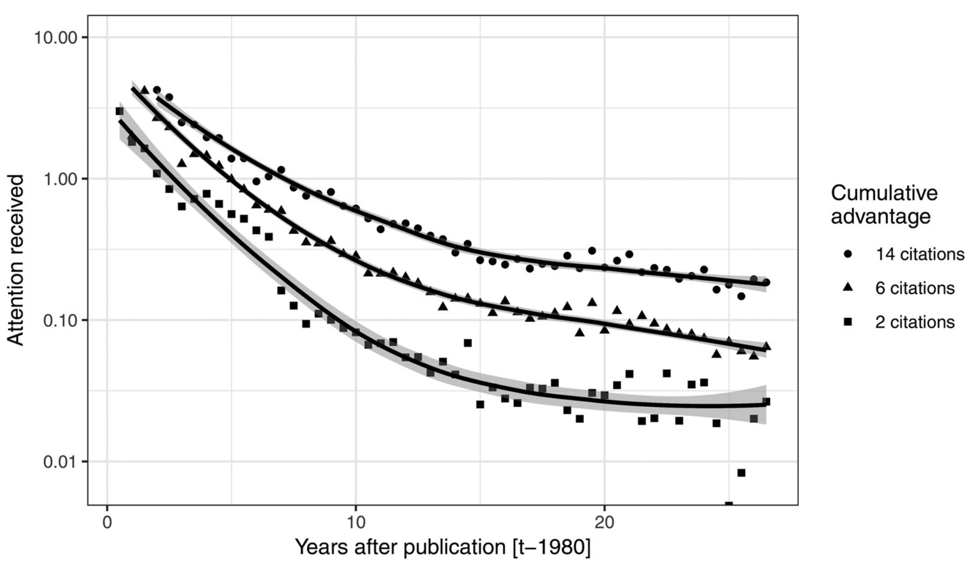
Appendix F

Model Fitting

We estimate the model variables using Equation 1 for u and v. The model is fitted using a nonlinear regression model. We fit a curve for each level of cumulative advantage. Figure F1 shows the fitting for all mechanical patents granted in 1980; dot shapes represent different levels of cumulative advantage measured as the number for accumulated citations. The model reproduces the data accurately with an $R^2 > .95$.

Figure F1

Model Fitting for All Mechanical Patents Granted in 1980



Note. Dot shapes represent different levels of cumulative advantage in terms of accumulated citations. The y-axis is in log-scale.

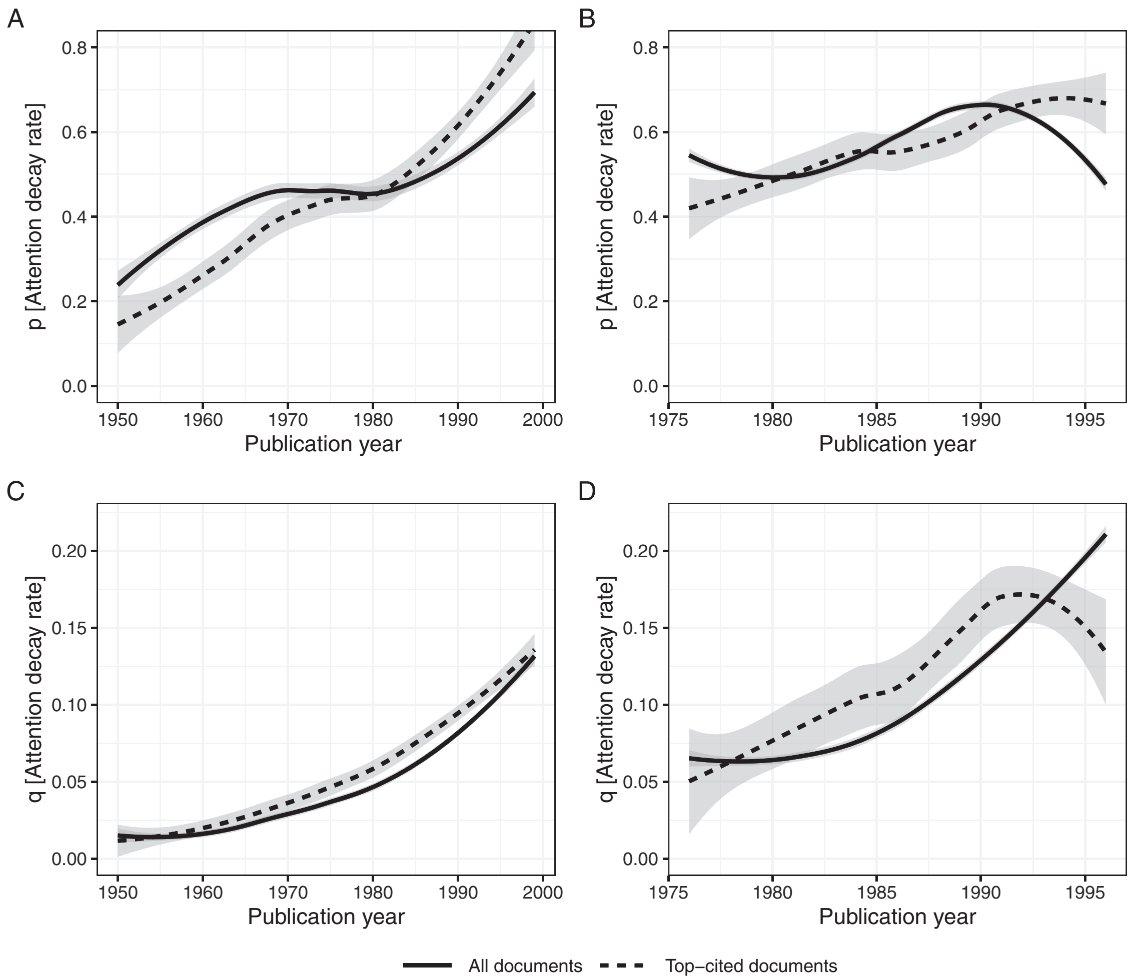
(*Appendices continue*)

Appendix G

Estimated Forgetting Rates

Figure G1

Forgetting Rates for American Physical Society (APS; Left Column) and United States Patent and Trademark Office (USPTO) Communities (Right Column)



Note. Solid lines represent all aggregated documents, and dashed lines represent the top-cited 15% of documents after t_c years. (A and B) are attention decay rates from communicative memory to oblivion (p). (C and D) are attention decay rates from cultural memory to oblivion (q).

Appendix H

Panel Data Analysis

Panel data analysis (PDA) is broadly used in social science to analyze multidimensional data involving observations over the same entities (USPTO categories and APS journals) over multiple periods (cohorts). A pooled model, which assumes that all observations are independent, is first estimated as $y_{it} = \alpha + \beta x_{it} + u_{it}$, where x_{it} is a vector of independent variables, and u_{it} is the error terms. However, the effects of independent variable could be driven by omitted variables, i.e., $cov(x_{it}; u_{it}) \neq 0$. Thus, the panel data structure of the data are exploited to provide evidence of the effects of independent variables beyond and above the entities'

(*Appendices continue*)

invariant characteristics and temporal changes. The within estimation follows the same general structure as the pooled model, but the error term is modeled as $u_{it} = c_i + \lambda_t + v_{it}$, where c_i absorbs all the invariant omitted variables across the grouping index i. λ_t absorbs all the temporal changes, and, v_{it} is the unobserved error term. The within estimator that considers just the entities' invariant effects (c_i) is called the one-way estimator, whereas the estimation that considers both entities (c_i) and temporal (λ_t) effects is called the two-ways estimator. The first difference estimator models the change in a variable from one measurement period to the next, aiming to eliminate the unobserved effects for each individual (Hsiao, 2007).

We conducted the Durbin–Wu–Hausman test (Greene, 2003) and the null hypothesis was rejected in all specifications (p-value $< .01$), leading us to select the fixed effects estimator instead of the random effects estimator for the analysis.

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