The Universal Decay of Human Collective Memory

C. Candia-Castro-Vallejos[a,b,c,*], C. Jara-Figueroa[a], Carlos Rodriguez-Sickert[c], Albert-László Barabási[b], and César A. Hidalgo[a,*]

[a]Collective Learning Group, The MIT Media Lab, Massachusetts Institute of Technology

[b]Network Science Institute, Northeastern University, Boston, MA 02115, USA

[c]Centro de Investigación en Complejidad Social (CICS), Facultad de Gobierno, Universidad del Desarrollo, Santiago, Chile.

[*]Corresponding Authors: hidalgo@mit.edu, ccandiav@mit.edu

May 17, 2018

Abstract

Collective memory is believed to decay through two mechanisms, one involving communicative memory–the memory sustained by oral communication–and another involving cultural memory–the memory sustained by the physical recording of information. Yet, there is no statistical evidence showing that collective memory decays through these two mechanisms, or exploring the universality of the decay function across a variety of cultural domains. Here, we use time series data on papers and patents' citations, and on the popularity of songs, movies, and biographies, to test the hypotheses that the decay of human collective memory involves the decay of communicative and cultural memory, and that the decay function is universal across all of these domains. We derive a mathematical model from first principles by formalizing these two mechanisms and show that the function predicted by this model provides a more accurate description of the data than previously proposed decay functions. Our results support the hypotheses that the decay of human collective memory involves the combined decay of communicative and cultural memory, and that the decay function is universal across multiple cultural domains. These findings allow us to explain the dynamics of the attention received by a piece of cultural content during its lifetime, and suggest that the dynamics of human collective memory follows a universal decay function.

Introduction

In what is probably Pablo Neruda's most famous poem–Poema 20–he wrote: "Es tan corto el amor, y tan largo el olvido" (Love is so short, and forgetting so long). Neruda's words express elegantly the fact that when in love people are constantly reminded of their loved ones, but once love fades, memories fade too. Inspired by Neruda we ask whether society also experiences the two phases of memory: an initial intense phase of remembrance followed by a longer and slower phase of forgetting. There is in fact, a vast literature exploring the decay of collective memory as a combination of two distinct processes [15, 2, 5, 4, 39, 13, 30, 31, 44, 32, 12]: the decay of communicative memory, normally sustained by the oral transmission of information, and the decay of cultural memory, which is sustained by the physical recording of information. This literature can provide inspiration for the construction of generative models of memory decay functions.

Yet, the theory of collective memory lacks quantitative models that would allow linking it to empirical data, such as the data developed in the literature of knowledge diffusion. Indeed, knowledge diffusion models the adoption and diffusion of cultural content as a combination of two processes [38, 18, 19, 37, 9, 14, 10]: a preferential attachment [6, 1] or cumulative advantage process [28, 43, 25], where popularity begets popularity, and a temporal decay function, which has been modeled using simple exponential [18] and log normal functions [38]. Overall, while there is consensus in the fact that cultural adoption should be modeled using a combination of preferential attachment and a temporal decay, there is no consensus on the exact shape of the temporal decay function or about its universality.

Here, we use data on scientific publications, patents, songs, movies, and biographies to test the hypothesis that the decay of collective memory is a process involving the decay of both, communicative and cultural memory. We formalize these ideas by constructing a mathematical model that allows us to compare a quantitative function with data on diverse forms of cultural production. We validate this model by showing that the bi-exponential function derived from it is statistically better at explaining the empirically observed decay of collective memory than the functions previously used in the literature, which lack a generative model. This finding validates the idea that the decay of collective memory is a process that results from the decay of both communicative and cultural memory. The model also makes observable both mechanisms and generalizes well to multiple data-sets, suggesting that it captures a universal feature of the decay of human collective memory.

Data and Methods

We use two types of data sources: time series data for scientific papers and patents, and cross-section data for songs, movies, and biographies. The American Physical Society (APS) corpus collects data about the attention pattern of physics articles from twelve different journals, between 1896 and 2016. For our analysis, we use a prospective approach (See SM 1.1) for all papers published between 1970 and 2003 in Physical Review Letters (PRL), and in Physical Review A to E [34, 33, 19]. The United States Patent and Trademark Office (USPTO) [17, 21] contains information about patents granted between 1976 and 2005. We use all patents granted between 1976 and 1995 in all categories: Chemical (CAT 1), Computers & Computation (CAT 2), Drugs & Medical (CAT 3), Electrical & Electronic (CAT 4), Mechanical (CAT 5) and Others (CAT 6). For both patents and papers we construct two time series, one for the number of citations obtained in each time window, and another for the accumulated citations obtained up to a given time. Our interest is to characterize the intrinsic dynamic of knowledge, therefore we deflate both time series by an inflation factor [19, 18] which accounts by the exponential increasing of the number of publications over time [38, 34] (See SM 1.2).

For songs, movies, and online biographies we use cross-section data, it means, data collected by observing songs movies and biographies at the same point of time. For songs, we use weekly ranking data from the "Hot-100 Billboard's ranking" [7] between October 1958 and July 2017. To measure online attention, we use Spotify's popularity index [35] taken on October 2016 and July 2017, and last.fm's play counts [24] for the last week of July 2017 (see SM2). We also collect data on $14,633$ movies released between 1937 and 2017 that have obtained more than 1,000 votes in the Internet Movie Database [20] as of July 2017. To measure the current popularity of movies we use the play counts for the trailer of each movie taken from YouTube [42]. For online biographies we focus on basketball, tennis, and Olympic medal winners. For basketball players, we consider the "Slam 500 Greatest NBA Players of All Times," for tennis players we consider the "Top 600 International males singles tennis player," and for Olympic medal winners we consider athletes who have won more than three gold medals. Current popularity was measured using the number of pageviews received by the Wikipedia biography [40] of each athlete between July 2016 and June 2017–for more information see SM 1.3 and 1.4.

Results

The literature on collective memory [16, 15, 3] suggests that the decay function should involve two mechanisms, an initial fast decay–signature of communicative memory–followed by a softer decline–resulting from cultural memory–(Figure 1 A). Using the distinction between communicative and cultural memory [16, 5, 3, 4] we propose a model where cultural memory and communicative memory co-exist, but decay at different rates.

We model the attention received by a cultural piece by assuming that the present day popularity S of a cultural piece is the sum of its popularity in both communicative memory u and cultural memory v. Hence, at any given time $S(t) = u(t) + v(t)$ (see Fig. 1 A). We assume that communicative and cultural memory decay independently with decay rates p for communicative memory and q for cultural memory, and that information flows from communicative memory to cultural memory at a rate r. Hence, communicative memory decays as $u(t+1) = (1-p)u(t) - ru(t)$ and cultural memory as $v(t+1) = (1-q)v(t) + ru(t)$. This defines the following system of differential equations:

$$S(t) = u(t) + v(t) \tag{1}$$

$$\frac{du}{dt} = -(p+r)u \tag{2}$$

$$\frac{dv}{dt} = -qv + ru. \tag{3}$$

We set the initial communicative memory $u(t=0) = N$ and we assume that at the beginning of the process there is no cultural memory associated to a new cultural product $(v(t=0) = 0)$–For more information see SM 2.1.

Using the initial conditions, we find that the solution of the system of equations is the bi-exponential function:

$$u(t) = Ne^{-(p+r)t} \tag{4}$$

$$v(t) = \frac{Nr}{p+r-q}\left(e^{-qt} - e^{-(p+r)t}\right) \tag{5}$$

$$S(t) = \frac{N}{p+r-q}\left[(p-q)e^{-(p+r)t} + re^{-qt}\right]. \tag{6}$$

Figure 1 B illustrates $S(t)$ for different values of the parameters, with $N = 1$, and Figure 1 C compares the bi-exponential function with the exponential [18, 19] and log-normal [38] decay functions proposed in previous literature (see SM 3 and 4).

We then apply the bi-exponential model to data by comparing it with the decay functions observed for paper and

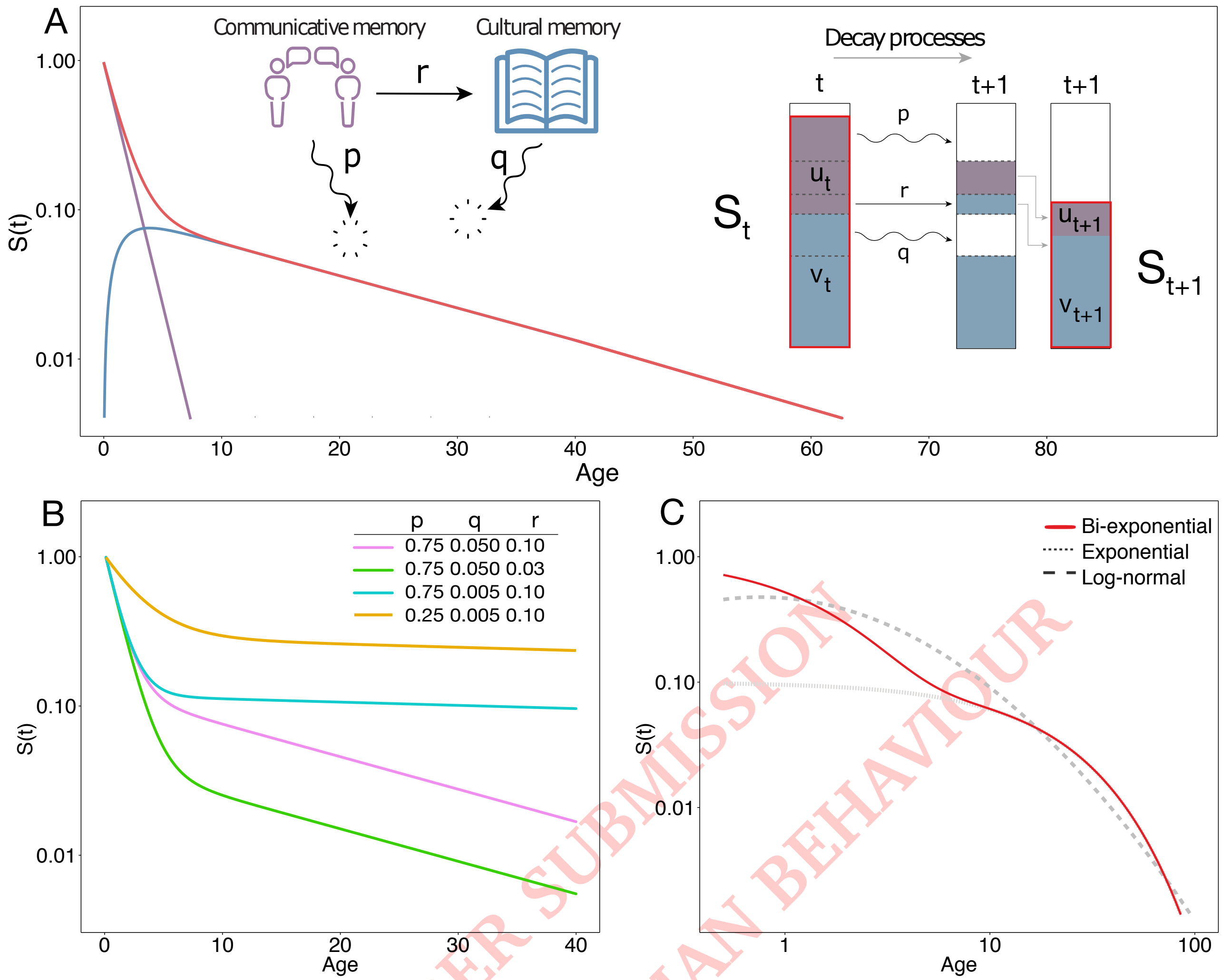

Figure 1: Modelling collective memory. **A** The red curve shows the bi-exponential function predicted by our model in log-lin scale. The light-blue and light-green curves show the two exponential of communicative and cultural memory. The inset illustrates the basic mechanics of the model. At any time point t the total memory is the sum of communicative memory u and cultural memory v. Both communicate and cultural memory decay with their own respective decay rates p and q. **B** The bi-exponential model (Eq. 6) for various parameters p, q, and r, can account for a wide range of decays. **C** Comparison between the bi-exponential model (in red), and the exponential and log-normal models in log-log scale.

patent citations, and for the online popularity of past music, movies, and biographies, with a comparable level of accomplishment. In the case of papers and patents, we group papers and patents with a similar number of cumulative citations. In the case of songs, movies, and biographies, these comparable sets are built into our selection criterion, since we study only songs that reached the Billboard ranking, biographies of award winning athletes, and movies that have received over 1,000 votes on IMDB. By respectively grouping papers, patents, songs, movies, and biographies, with a similar level of accomplishment, we control for differences in preferential attachment and isolate the temporal decay of collective memory.

Figure 2 shows the average number of new citations obtained by scientific papers (A, B, C, and D) and patents (E and F) for different levels of accumulated citations k. The red lines show the fit of the bi-exponential model, whereas the dashed and dotted lines show, respectively, the the log-normal and exponential decays used in [38] and [18]. In all cases, we find that, after choosing papers and patents with the same level of cumulative citations, the

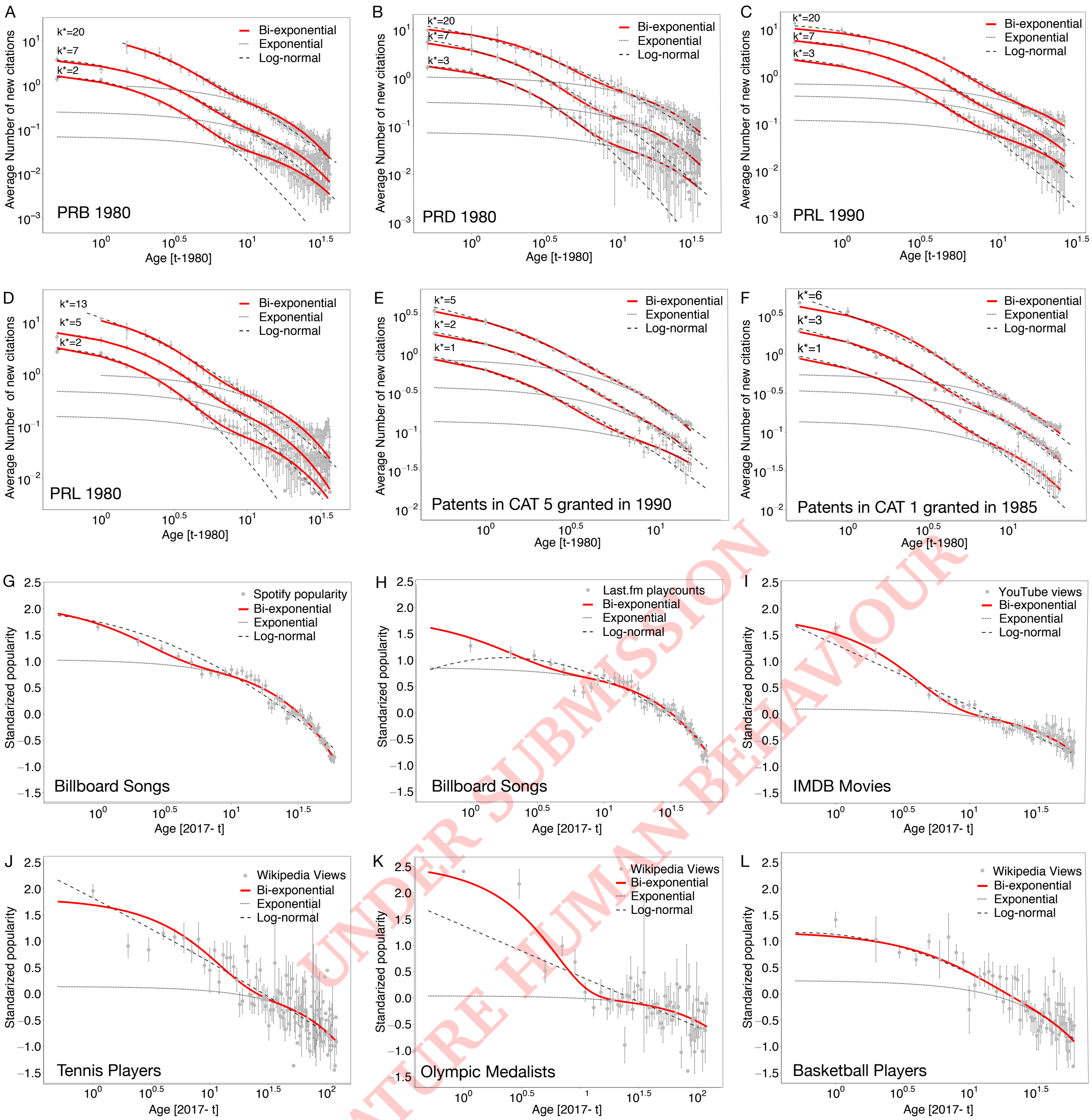

Figure 2: The universal decay of collective memory. Average number of new citations received by **A** All papers published in Physical Review B in 1980, **B** All papers published in Physical Review D in 1980, **C** All papers published in Physical Review Letters in 1990, **D** All papers published in Physical Review L in 1980, **E** All Mechanical patents granted in 1990, and **F** All Chemical patents granted in 1985. Next, for cultural pieces we have the standardized popularity of **G** Songs based on spotify's popularity index (y-axis) as a function of the date the song first appeared in the Billboard ranking (x-axis). **H** Songs based on Last.fm's play counts (y-axis) as a function of the date the song first appeared in the Billboard ranking (x-axis). **I** Movies based on YouTube's view counts (y-axis) as a function of the date the movie was released (x-axis). **J** Tennis players based on Wikipedia's page views (y-axis) as a function of the date that the tennis player was included in the Top 600 International males singles tennis player (x-axis). **K** Olympic medalist based on Wikipedia's page views (y-axis) as a function of the date of the middle of the career of the Olympic medalist. **L** Basketball players based on Wikipedia's page views (y-axis) as a function of the date that the Basketball player starts his career (x-axis). Red lines show our bi-exponential model fit, whereas the dashed lines and dotted lines show the log-normal decay used by [38] and the exponential decay used by [18]. Error bars represent standard errors.

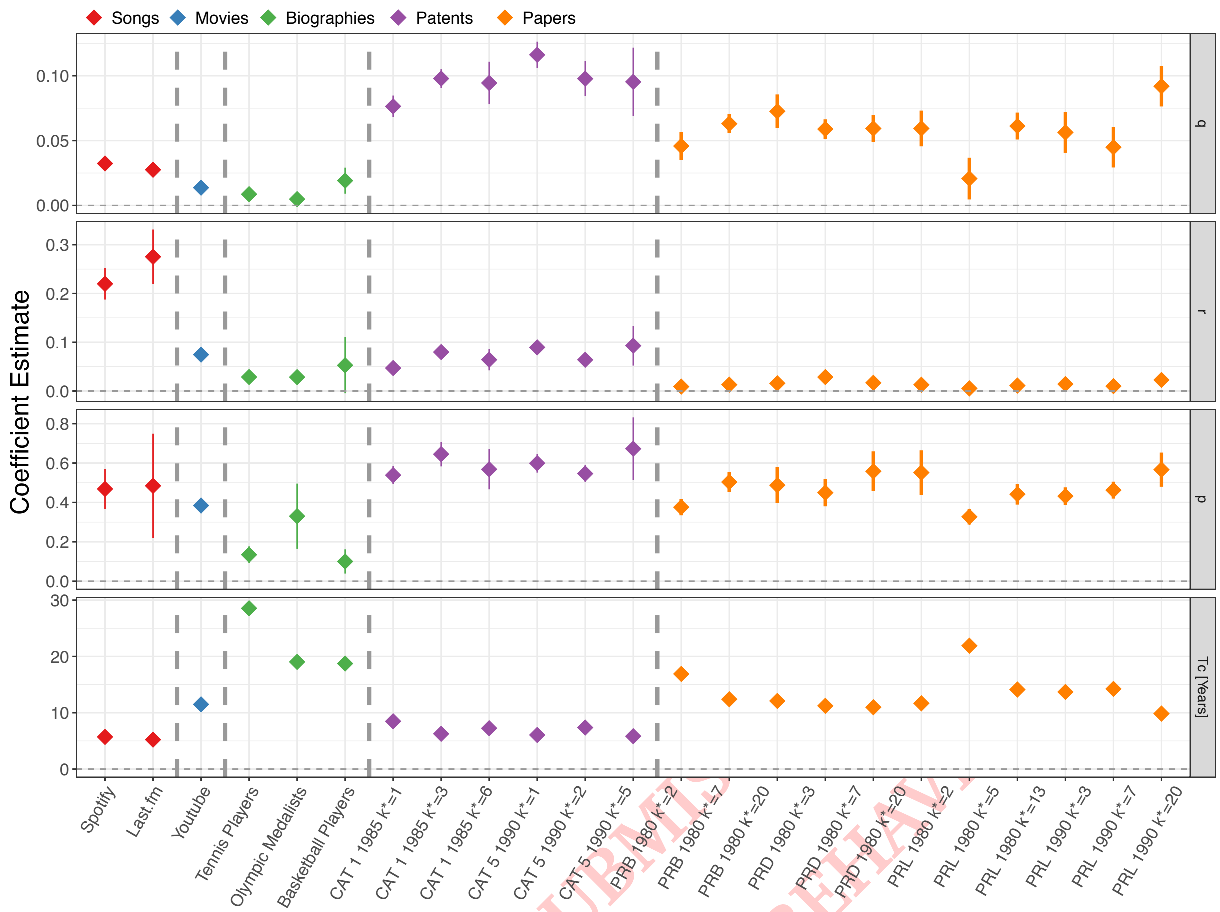

Figure 3: Model's parameters described by Eq. 6, and showed on figure 2. The critical time (D), t_c, is calculated by Eq. 7, and it is measured in years. Each box correspond to a model's parameter and colors represent the type of cultural piece. Bars represent the standard deviation of the coefficient estimation.

bi-exponential model captures the temporal pattern of human collective forgetting accurately (see SM section 3.4 for AICc comparison of fits for data on all years, journals, and categories). More importantly, in several of these empirical curves the shoulder of the bi-exponential curve is clearly visible, so the model helps unveil the point at which cultural memory takes over communicative memory.

We observe a similar behavior when we apply the bi-exponential model to data on music, movies, and biographies. Since we lack time series data for these three sources, we look at the present day popularity of music, movies, and biographies as a function of their age. For songs, we determine age using the year they first reached the billboard ranking. For movies, we calculate age using their release year. For the biographies of athletes we use as the age of the accomplishment the time when they were introduced in their respective international rankings. Once again, when we compare our model with the previously proposed log-normal (dashed lines) and exponential models (dotted lines) (Figure 2 G-L), we find that the bi-exponential model provides a more accurate fit to the data, since it captures the initial fast decay of communicate memory followed by the slow decay of cultural memory. Also, it visible captures the transition from communicative to cultural memory.

Together, the data on papers, patents, songs, movies, and biographies, shows that this bi-exponential decay is universal across all domains. Yet, the parameters of the decay function are different for papers, patents, songs, movies, and biographies. We therefore, compared the model parameters (p, q, r, and t_c) across all studied domains (Figure 3). Here t_c is the time at which cultural memory overtakes communicate memory, which, according to the model can be approximated as (see SM 2.2 and 2.3):

$$t_c = \frac{1}{p+r-q} \log\left(\frac{(p+r)(p-q)}{rq}\right). \tag{7}$$

Although our analysis and results suggest that the shape of the decay in attention function is universal across multiple cultural domains, its parameters are informative of the domain-specific decay dynamics (Figure 3). When comparing the parameters, we find that the the decay rates of communicative memory are much larger than those of cultural memory ($p >> q$) as suggested by the literature [2] (Figure 3 A and C). Also, we find that communicative memory decays much faster for music and movies than for biographies (Figure 3 C), resulting in critical times that are relatively low for music, movies, and papers (5 to 10 years, Figure 3 D), and much longer for biographies (15 to 30 years). It means, for biographies, the era dominated by communicative memory lasts longer than the era dominated by cultural memory.

In order to explain these differences, two aspects of the underlying dynamics of collective memory need to be considered: i) the support system of each mechanism and ii) the nature and dynamics of network externalities in their consumption. Greater network externalities imply that your consumption of the cultural piece increases more with concurrent consumption and thus heightens the effect of communicative memory on the dynamics of collective memory. Take the case of artistic cultural pieces. Once a movie is released we go together to the theatres and talk about it when we meet our friends. Recently released songs are played on the radio and in discotheques. Indeed, carrying capacity for this collective love is limited. Both songs and movies have a relatively high rate of transfer, r (3 B), from communicative to cultural memory, but movies have larger t_c than songs, probably because of the dynamism of music industry. For athletes, in contrast, network externalities by the occasional documentary retrospective are mainly at work when sports events in which athletes participate take place. Given that athletes are accumulating accomplishments over time, they are more likely to be highly remembered while their careers are active, in average 20 years. After that, they are remembered mainly through cultural memory. In fact, for as much as a couple of decades after their main accomplishment.

Together, these results show that the bi-exponential decay predicted from formalizing the mechanisms suggested by the literature on collective memory provide a universally good approximation for the decay of memory across a wide variety of cultural domains.

Discussion

Decades ago Neruda observed that love was short and intense, while forgetting moved slowly into oblivion. Here, we build on the ideas of communicative and cultural memory to show that the decay of human collective memory follows a universal decay function that is characterized by two phases. We show that the shape of this function is universal across a variety of cultural domains, but that its parameters are informative of the forgetting dynamics of specific systems. These findings quantitatively validate the ideas of communicative and cultural memory, and allow us to better understand how societies forget.

For decades scholars have been using papers and patents citations to study the spread and adoption of ideas and cultural content [11, 29, 23, 38, 34, 22, 8, 41, 36, 26, 27, 18, 19]. Yet, while there is consensus on the fact that preferential attachment processes contribute to the spread of popular pieces, there is no consensus on the nature of the functional form capturing the decay of attention. Mathematically, the temporal decay curves describing the number of citations or attention $A(t)$ received by a paper, patent, or piece of cultural content (Figure 4 A) can be expressed as a function of two parameters: (i) its age t, and (ii) the cumulative citations received by that paper, patent, or cultural piece k. Formally, it has been shown that $A(t)$ is separable [38, 18, 37, 9, 14, 10], as $A(t) = c(k) \times S(t)$, where $c(k)$ captures the effects of preferential attachment (Figure 4 B) and $S(t)$ captures the temporal decay (Figure 4 C).

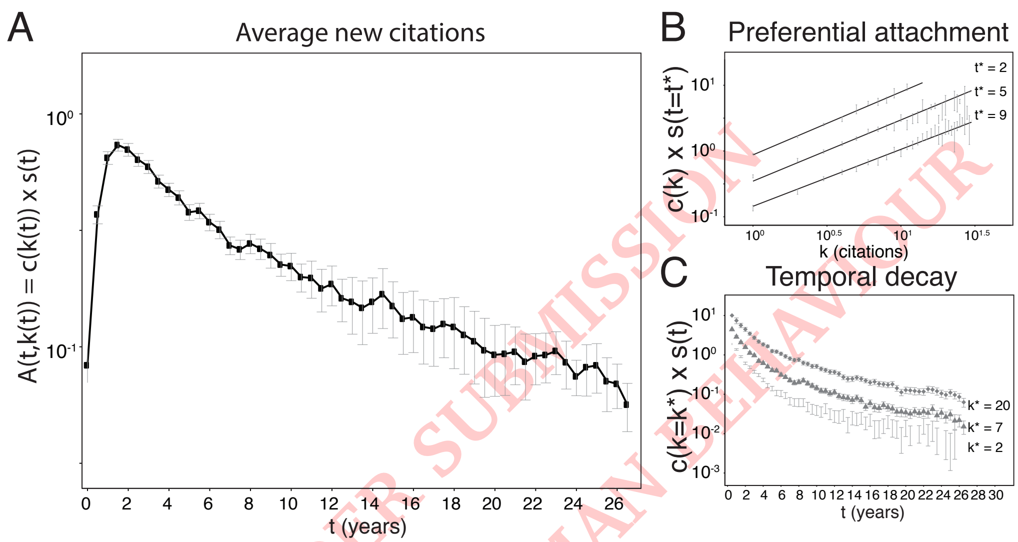

Figure 4: Universal patterns in the decay of human collective memory. **A** Average number of citations received each semester by papers published in physical review B ($A(t)$). **B** Average number of citations received by a paper as a function of the cumulative citations received by that paper ($\propto c(k)$). Different curves represent different ages, **C** Average number of citations received by papers with the same number of cumulative citations as a function of their age ($\propto S(t)$). Different curves represent groups of papers with a different number of total citations.

The solid line (Figure 4 A) shows the average number of citations received by papers published in Physical Review B in 1990 ($A(t)$) as a function of their age. $A(t)$ describes the traditional increase and decline known to characterize knowledge diffusion or cultural product adoption curves [18, 37, 9, 14, 10].

Figure 4 B shows the preferential attachment component, by presenting the number of new citations (Δc) received by a paper as a function of its cumulative citations ($c(k)$) [6, 1]. Figure 4 C shows the temporal decay component ($S(t)$), representing the number of new citations received by papers with the same number of cumulative citations $k = k^*$ as a function of their age. That is, the dashed lines show papers for which the effect of preferential attachment is kept constant: $A(t)|_{k=k^*} = c(k^*) \times S(t)$. Here, we observe the initially fast decay followed by a milder decline.

But what gives rise to this unorthodox decay function? Our results indicate that the fast decay followed by a mild decline observed in these empirical decay functions is the result of a universal bi-exponential curve that can be derived from first principles by distinguishing two concepts rooted in the literature on collective memory: communicative and cultural memory [15, 2, 5, 4, 39, 13, 30, 31, 44, 32]. The agreement between this model and the empirical data validates these theoretical mechanisms and offers a mean to measure the model parameters. Interestingly, we find that while the shape of the decay function is universal, its parameters are informative of the decay dynamics of specific systems (Figure 3). For instance, compared to songs, movies, papers, and patents; biographies have relative large critical times (t_c), meaning that athletes are remembered mainly through oral culture for as much as a couple of decades after their main accomplishment. Songs, on the other hand, have a relatively high rate of transfer (r) from communicative to cultural memory, suggesting that the fast decay of songs from communicative memory is dampened by the rapid reproduction of music in cultural memory –for more implications and comments see SM 5.

Our results support the hypotheses that the decay of human collective memory involves the combined decay of communicative and cultural memory, and that the decay function is universal across multiple cultural domains. These findings allow us to explain the dynamics of the attention received by a piece of cultural content during its lifetime, and suggest that the dynamics of human collective memory follows a universal decay function.

Acknowledgments

C. C-C-V. and C. R-S. acknowledges the financial support from Centro de Investigación en Complejidad Social (CICS) and Universidad del Desarrollo. C. J-F. and C.A.H. acknowledge support from the MIT Media Lab Consortia. The authors are also thankful to Flavio Pinheiro, Tarik Roukny, the Centro de Investigación en Complejidad Social (CICS), the Collective Learning Group at the MIT Media Lab, and the Center for Complex Network Research (CCNR) at Northeastern University for the helpful insights and discussions.

Author Contributions

C. C-C-V. contributed to study conception and design, acquisition of data, analysis and interpretation of data, and drafting of manuscript; C. J-F. contributed to acquisition of data, interpretation of data, and drafting of manuscript; C. R-S. contributed to study conception and design, and interpretation of data; A-L. B. contributed to study conception and design, drafting of manuscript, and critical revision; C. A. H. contributed to study conception and design, interpretation of data, and drafting of manuscript.

Data Availability

The datasets from the American Physical Society, analyzed during the current study is available in the APS Data Sets for Research repository, under request https://journals.aps.org/datasets.

The datasets of United State Patents analyzed during the current study is available in the NBER repository, http://www.nber.org/patents/.

The datasets for Songs, Movies, and Biographies generated during and analyzed during the current study are available from the corresponding authors on reasonable request.

References

[1] Réka Albert and Albert-László Barabási. “Statistical mechanics of complex networks”. In: *Reviews of Modern Physics* 74.1 (Jan. 2002), pp. 47–97.

[2] Jan Assmann. “Collective Memory and Cultural Identity”. In: *New German Critique* 65 (1995), pp. 125–133.

[3] Jan Assmann. “Communicative and Cultural Memory”. In: *Cultural Memory Studies. An International and Interdisciplinary Handbook* (2008), pp. 109–118.

[4] Jan Assmann. “Communicative and cultural memory”. In: *Cultural Memories*. Springer, 2011, pp. 15–27.

[5] Jan Assmann. *Das kulturelle Gedächtnis. Schrift, Erinnerung und politische Identität in frühen Hochkulturen.* Verlag C.H. Beck, 2007, pp. 9–27.

[6] Albert-László Barabási and Réka Albert. “Emergence of Scaling in Random Networks”. In: *Science* 286.5439 (Oct. 1999), pp. 509–512.

[7] Billboard. *Billboard Magazine The Hot 100 Ranking*. 2016.

[8] Johan S G Chu and James A Evans. *Too Many Papers? Slowed Canonical Progress in Large Fields of Science*. Mar. 2018.

[9] Gábor Csárdi et al. “Modeling innovation by a kinetic description of the patent citation system”. In: *Physica A: Statistical Mechanics and its Applications* 374.2 (Feb. 2007), pp. 783–793.

[10] S. N. Dorogovtsev and J. F. F. Mendes. “Evolution of networks with aging of sites”. In: *Phys. Rev. E* 62 (2 Aug. 2000), pp. 1842–1845.

[11] Santo Fortunato et al. “Science of science”. In: *Science* 359.6379 (2018).

[12] Ruth García-Gavilanes et al. “The memory remains: Understanding collective memory in the digital age”. In: *Science Advances* 3.4 (2017).

[13] Arthur Goldhammer, Pierre Nora, and Lawrence D. Kritzman. *Realms of Memory: The Construction of the French Past*. Vol. 3. Columbia University Press, 1998.

[14] Michael Golosovsky and Sorin Solomon. “Stochastic Dynamical Model of a Growing Citation Network Based on a Self-Exciting Point Process”. In: *Physical Review Letters* 109.9 (Aug. 2012), p. 098701.

[15] Maurice Halbwachs. *La mémoire collective*. Albin Michel, 1997.

[16] Maurice Halbwachs. *On Collective Memory*. University of Chicago Press, 1992, p. 244.

[17] Bronwyn H. Hall, Adam B. Jaffe, and Manuel Trajtenberg. *The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools*. NBER Working Papers 8498. National Bureau of Economic Research, Inc, Oct. 2001.

[18] K. W. Higham et al. “Fame and obsolescence: Disentangling growth and aging dynamics of patent citations”. In: *Physical Review E* 95.4 (2017).

[19] K.W. Higham et al. “Unraveling the dynamics of growth, aging and inflation for citations to scientific articles from specific research fields”. In: *Journal of Informetrics* 11.4 (2017), pp. 1190–1200.

[20] IMDB. *The Internet Movie Database*. 2017.

[21] A. B. Jaffe, M. Trajtenberg, and R. Henderson. “Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations”. In: *The Quarterly Journal of Economics* 108.3 (Aug. 1993), pp. 577–598.

[22] Molly M. King et al. “Men Set Their Own Cites High: Gender and Self-citation across Fields and over Time”. In: *Socius* 3 (2017), p. 2378023117738903.

[23] Tobias Kuhn, Matja ž Perc, and Dirk Helbing. “Inheritance Patterns in Citation Networks Reveal Scientific Memes”. In: *Phys. Rev. X* 4 (4 Nov. 2014), p. 041036.

[24] Last.fm. *Last.fm Web API*. 2017.

[25] Robert K. Merton. “The Matthew Effect in Science, II: Cumulative Advantage and the Symbolism of Intellectual Property”. In: *Isis* 79.4 (1988), pp. 606–623.

[26] Satyam Mukherjee et al. “How Atypical Combinations of Scientific Ideas Are Related to Impact: The General Case and the Case of the Field of Geography”. In: *Knowledge and Networks*. Ed. by Johannes Glückler, Emmanuel Lazega, and Ingmar Hammer. Cham: Springer International Publishing, 2017, pp. 243–267.

[27] Satyam Mukherjee et al. “The nearly universal link between the age of past knowledge and tomorrow’s breakthroughs in science and technology: The hotspot”. In: *Science Advances* 3.4 (2017).

[28] Derek De Solla Price. “A general theory of bibliometric and other cumulative advantage processes”. In: *Journal of the American Society for Information Science* 27.5 (Sept. 1976), pp. 292–306.

[29] Filippo Radicchi, Santo Fortunato, and Claudio Castellano. “Universality of citation distributions: Toward an objective measure of scientific impact”. In: *Proceedings of the National Academy of Sciences* 105.45 (2008), pp. 17268–17272.

[30] HL Roediger and KA DeSoto. “Forgetting the presidents”. In: *Science* 346.6213 (2014), pp. 1106–1109.

[31] HL Roediger, Franklin M Zaromb, and Andrew C Butler. “The role of repeated retrieval in shaping collective memory”. In: *Memory in mind and culture* (2009), pp. 29–58.

[32] David C. Rubin. “How quickly we forget”. In: *Science* 346.6213 (2014), pp. 1058–1059.

[33] H.-W. Shen and A.-L. Barabasi. “Collective credit allocation in science”. In: *Proceedings of the National Academy of Sciences* 111.34 (Aug. 2014), pp. 12325–12330.

[34] R. Sinatra et al. “Quantifying the evolution of individual scientific impact”. In: *Science* 354.6312 (Nov. 2016).

[35] Spotify. *Spotify Web API*. 2017.

[36] Brian Uzzi et al. “Atypical Combinations and Scientific Impact”. In: *Science* 342.6157 (2013), pp. 468–472.

[37] Sergi Valverde et al. “Topology and evolution of technology innovation networks”. In: *Physical Review E* 76.5 (Nov. 2007), p. 056118.

[38] Dashun Wang, Chaoming Song, and Albert-László Barabási. “Quantifying long-term scientific impact.” In: *Science (New York, N.Y.)* 342.6154 (2013), pp. 127–32.

[39] James V Wertsch. *Voices of Collective Remembering*. Cambridge University Press, 2002.

[40] Wikipedia. *The Free Encyclopedia*. 2017.

[41] Soon-Hyung Yook, Filippo Radicchi, and Hildegard Meyer-Ortmanns. "Self-similar scale-free networks and disassortativity". In: *Phys. Rev. E* 72 (4 Oct. 2005), p. 045105.

[42] YouTube. *YouTube Web Platform*. 2017.

[43] G. Udny Yule. "A Mathematical Theory of Evolution, Based on the Conclusions of Dr. J. C. Willis, F.R.S." In: *Philosophical Transactions of the Royal Society of London. Series B, Containing Papers of a Biological Character* 213 (1925), pp. 21–87.

[44] Franklin Zaromb et al. "Collective memories of three wars in United States history in younger and older adults". In: *Memory & cognition* 42.3 (2014), pp. 383–399.