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Cultural Attraction in Film Evolution: the Case of Anachronies

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Abstract

In many films, story is presented in an order different from chronological. Deviations from the chronological order in a narrative are called anachronies. Narratological theory and the evidence from psychological experiments indicate that anachronies allow stories to be more interesting, as the non-chronological order evokes curiosity in viewers. In this paper we investigate the historical dynamics in the use of anachronies in film. Particularly, we follow the cultural attraction theory that suggests that, given certain conditions, cultural evolution should conform to our cognitive preferences. We study this on a corpus of 80 most popular mystery films released in 1970–2009. We observe that anachronies have become used more frequently, and in a greater proportion of films. We also find that films that made substantial use of anachronies, on average, distributed the anachronies evenly along film length, while the films that made little use of anachronies placed them near the beginning and end. We argue that this can reflect a functional difference between these two types of using anachronies. The paper adds further support to the argument that popular culture may be influenced to a significant degree by our cognitive biases.

Keywords

cultural evolution – cultural attraction – film – curiosity – narrative structure

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1 Introduction

500 Days of Summer (2009) is a romantic Hollywood comedy about a relationship between a man named Tom and a woman named Summer. Their story begins on the day when they first meet each other, and ends on day 500, when Tom encounters another woman. A chronological order of narration – from the first day to the last – might seem natural in this case, but it is not the order in which the story is presented. Instead, it is told in a sequence that may look random: day 488, then day 1, 290, 1, 3, 4, 8, 154, 11, 22, 27, 28, 31, 282, 34, and so on. You might have encountered this kind of "jumping" plot – probably in a less extreme form – in other films too. In narratology, the discipline studying the composition of stories, such shifts in chronological order are called anachronies (Genette, 1980; Prince, 2003).

Anachronies are widespread in contemporary complex narratives, like novels (Sternberg, 1978), but not so typical of older narrative forms, like folk narratives: most folktales seem to be told in a strict chronological order, without any "jumps" (Propp, 1968). Film historians, too, regard complex temporal structures, like the one in *500 Days of Summer*, as indicating narrative "complexity", typical of the movies since the 1990s, but not of the preceding film history (Buckland, 2009, 2014; Cameron, 2008).[1] Nevertheless, to our knowledge, there has been no attempt to assess this supposed increase of complexity through quantitative methods. Also, we are not aware of any systematic explanation of this expected increase in temporal complexity.

In this paper, we intend to fill in these gaps, which would mean (1) providing quantitative evidence for the growth of anachronies and (2) suggesting a likely theoretical explanation of this growth. We will use popular Hollywood films as our research object, although we suspect that the growth of anachronies could be found in other types of narratives too. The theoretical explanation, as well, will not be confined to films; it will aim at answering the more general question: why do anachronies become more widespread in popular narratives?

1.1 *Theory*

The expectation that anachronies are becoming increasingly widespread in contemporary narratives (including film narratives) is grounded in the theory

1 It must be noted that verbal narration is well-suited for quick "jumps" between past, present, and future – even within a single sentence – while visual narration may be less convenient for this purpose: it requires additional, often not so intuitive, indicators (e.g., flashbacks can be indicated by blurs, fades, dissolves, color change, etc.). This may also explain the late spread of anachronies in films.

of cultural evolution (Mesoudi, 2011; Richerson & Christiansen, 2008), particularly in the evolutionary theory of cultural attraction (Sperber, 1996; Cladiere, Scott-Phillips, & Sperber, 2014). One of the claims of this theory is that the evolution of cultural information is to a substantial extent influenced by cultural attractors: systematic biases that tendentially favor transformation and transmission of the information in a particular direction. The causal factors that produce such biases can be different, but the most studied ones are cognitive factors (Morin, 2011).

The potential role of cognitive factors of attraction has been investigated in a number of studies. In a study of European paintings, Olivier Morin (2013) has demonstrated that during the 15th–20th centuries the proportion of portraits with the "direct gaze" – that is, portraits that as if look directly at the spectators – significantly increased. A suggested explanation of this increase is that humans find direct gaze more cognitively "attractive", as was demonstrated in independent experimental studies (Conty, Gimmig, Belletier, George, & Huguet, 2010; Conway, Jones, DeBruine, & Little, 2008). Similar instances of cognition driving the evolution of culture were suggested for many other objects: religious beliefs (Atran, 2002), urban legends (Heath, Bell, & Sternberg, 2001; Stubbersfield, Tehrani, & Flynn, 2017), fairy tales (Norenzayan, Atran, Faulkner, & Schaller, 2006; Loewenstein & Heath, 2009), quotations in online blogs (Lerique & Roth, 2017), and others. Films, too, were argued to adjust to our cognitive preferences: for instance, over the course of the 20th century films became "quicker, faster, darker" (Cutting, Brunick, DeLong, Iricinschi, & Candan, 2011; Cutting & Candan, 2015): the average shot length decreased from 10 to 4 seconds, the amount of movement and optical change on screen increased too, while the brightness of film image decreased. It is plausible that these changes were driven by the way human attention works: fast movements and dark colors are the stimuli that capture our visual attention.

We suggest that anachronies have become increasingly widespread in the films like *500 Days of Summer* due to a similar process of cognitive attraction. It has been demonstrated that stories containing anachronies are perceived as more interesting than equivalent stories without anachonies (Brewer & Lichtenstein, 1981, 1982; Brewer, 1985). Thus, we could expect a cognitive attraction towards highly anachronic film plots. Such plots would probably have larger chances to be appreciated, which could in turn motivate film producers to use anachronies even more often. That is why we can expect an increasing trend in the use of more complex – anachronic – stories in film history.

Why would introducing an anachrony into a story make this story more interesting? It has been experimentally shown that by simply changing the order of events in a narrative – by putting the later events *before* the ones that happened earlier – we can make this narrative more intriguing (Hoeken & Vliet, 2000). Here is an example created by analogy with those used in the experimental studies of narrative interest, which demonstrates the cognitive function of anachronies:

> *Tom met Summer on a regular working day. This encounter would change his life.*

This is a micro-story in which two utterances are present in a chronological order. However, we could begin this story differently:

> *This encounter would change Tom's life.*

By doing so, we open up what George Loewenstein has called an "information gap" (Loewenstein, 1994): we push the readers to ask themselves: "Why would Tom's life change? An encounter with whom?" If the answers to these questions seem important enough, readers may become curious. Their curiosity should be at least partly satisfied with the answer:

> *He met Summer on a regular working day.*

In this example, presenting the events in the order that is chronologically wrong – anachronic – allows opening up an information gap.

It has been argued in neuroscientific studies that such an information gap acts as a motivating catalyst in our cognition: the state of curiosity anticipates a reward that is provided when the information sought for is acquired (Kang et al., 2009; Kidd & Hayden, 2015). It has been suggested that the experience of curiosity may be generally pleasant, especially when an individual feels that they have been deprived of information (Litman, 2005).

If the experience of curiosity is associated with an anticipated pleasurable rewarding, we would expect individuals to seek for this experience. In the case of art history, we would thus expect curiosity-evoking narratives to be cognitively attractive. Therefore, over time films should adjust to this cognitive preference and become better at evoking curiosity in viewers. This greater capability of evoking curiosity can have two manifestations. One is the mentioned *quantitative* change: films could tend to use anachronies more frequently. However, it is also possible that we could observe some *qualitative* change in the use of anachronies: films could develop new (probably, more effective) techniques of using anachronies to evoke curiosity.

Therefore, we suggest two hypotheses. The *quantitative increase* hypothesis predicts that the attraction towards more curiosity-triggering stimuli increases the number of anachronies in films. The *qualitative change* hypothesis, which is more tentative, predicts that we may find some qualitative shift in the use of anachronies, making them more effective in evoking curiosity.

2 Materials and Methods

2.1 *Sample*

Finding trends in artistic data (films, literature, music, etc.) can be especially difficult as these cultural domains tend to value originality and avoidance the common paths. This task becomes especially problematic if the data must be hand-coded, which can be labor-intensive (as it was in our case). For this reason, to study the impact of a potential curiosity bias, we decided to choose a "model genre" of film – similarly to how model organisms are used in biology. We chose to focus on the genre of "mystery" films, as mystery films typically revolve around a solution of a problem or a crime (Bordwell, 2006) and are likely candidates for films where the curiosity bias would be most clearly visible. In these films the narration is often composed to include suspense, and the use of anachronies is an easy technique to introduce.

We compiled a sample of the *most popular* mystery films from 1970 to 2009 to represent cultural trends in film production. For cultural artefacts like films, a subset of most popular items can be a revealing sample of the biases involved in cultural evolution, as they are both produced for the purpose of becoming popular and selected for by a large number of people. The films that end up among the most popular are thus likely to carry a strong signal of the cognitive biases involved in their production and reception. Limiting to only the most popular subset also makes the data collection less labor-intensive.

Samples of the most popular items are often used in film studies to indicate popular trends for viewers and producers. Usually, these studies consider films with the highest box-office gross (e.g., see Redfern, 2014). However, box-office data can be strongly influenced by marketing: high gross profit can simply be a sign of good promotion campaign, not the popular opinion about a film. Thus, instead of box-office data, we used crowd-sourced ratings from the Internet Movie Database (IMDb), as over time they should converge on what the viewers find most appealing.

To establish a temporal range, we divided the time from 1970 to 2009 into 5-year periods, and for each period we took 100 films with the highest MOVIEmeter ranking for each. MOVIEmeter is a ranking system that measures popularity of every film based on a proprietary algorithm that aggregates a number of website indicators. Out of these 100 films per each 5 years, we took 10 with the highest "user ranking", that is, the average score showing how much the viewers (IMDb users) liked or disliked the film. Data were collected in November 2014. For example, *500 Days of Summer* is currently rated as 7.7 (out of 10) based on 411,736 user rankings (as of December 9, 2017). As a result, we sampled 80 films distributed over 40 years.

2.2 *Annotation of the Sample*

Each film was manually annotated for anachronies by one researcher following oral instructions. The researchers were aware of the purpose of the study, however the object is easy to recognize and does not leave much room for ambiguity in annotation. Each anachrony was also given a timestamp in film time. This allowed us to analyze two things: 1) the frequency of anachronies in the film, i.e., anachronies per hour; 2) the location of these anachronies within each film. Mean film duration in the sample was 115 minutes, adding up to a total of ~153 hours of film time that were collectively annotated.

2.3 *Data Analysis*

For data analysis, we applied ordinary least squares linear regression modelling with model criticism (Baayen, 2008) and quantile regression modelling (Koenker, 2005, 2017). Quantile regression is a semi-parametric technique that fits regression curves on several quantiles of the response variable conditional on the predictor variable. Quantile regression is frequently used for analyzing ecological datasets with heterogeneous variation, where some unrecorded limiting factor may influence part of the observed variation (e.g., Cade & Noon, 2003; Cade, Noon, & Flather, 2005). Thus, when not all relevant factors are measured or included in analysis, the relationship between the mean of the response variable and the predictive factors can be weak or missing, however meaningful and stronger predictive relationships can actually be found with parts of the distribution (Terrell, Cade, Carpenter, & Thompson, 1996; Cade, Terrell, & Schroeder, 1999; Cade & Noon, 2003).

Quantile regression allows an improvement to the former by fitting regression equations to different quantiles of the data. For temporal data, as is ours, it allows the heterogeneous variation to be described in terms of different growth rates for parts of the data: for example, data later in time can show a greater increase in higher quantiles of the data than lower quantiles. In this case, regression to the mean may be a biased and a less informative estimation of the data.

For the analysis, we determined the range of reliable extreme quantiles, based on the sample size following Rogers' guidelines (Rogers 1992), to be 0.10 and 0.90 and applied quantile regression on every 0.05 quantiles between these extremes. We estimated the standard errors and p-values for 5 of these quantiles throughout the dataset – 0.10, 0.25, 0.50, 0.75, 0.90 – using a bootstrap method with 10,000 replacements as described in Koenker (1994).

In ecology, quantile regression offers good models when the relative rank of the data points would explain their behavior (e.g., when the smallest animals would be eaten by predators). However, especially with small samples, the effect may be tied not to rank exactly, but to a type or a variety of data points (e.g., when relatively small animals are likely to get eaten). This effect can hold even if their relative abundance will change (e.g., medium-size animals might be relatively safe even if the small animals are not abundant). Accordingly, the causal effects may be tied to the relative variety of data points, not their exact rank. To analyze this possibility in our data, we applied *k*-means clustering to divide the films over time into several groups. We then applied linear regression modelling, informed by these groups, to analyze possibly diverging trends between the types of films.

For qualitative differences in the function of anachronies we analyzed films in terms of the location of their anachronies. For this, we used the clusters from regression modelling and qualitatively analyzed the functions for particular films.

Statistical analyses were performed in R, v 3.3.2 (R Core Team, 2016). The quantile regressions were performed using the package Quantreg 5.33 (Koenker, 2017). *K*-means clustering was performed using the Hartigan and Wong (1979) algorithm in the *kmeans* function in the base package in R. The analysis itself is reproducible with the data and the code provided in the supplementary materials.

3 Results

3.1 *Quantitative Increase*

The raw data are plotted in Figure 1 (for individual films see also Table 1 in Supplement A). The mean number of anachronies per hour (an/h) shows an increase from 3.5 to 11.8, which mostly happened in the late 1990s. The data has a positive skew throughout the period: many films used close to the minimum number of anachronies while there were a number of films that used many more anachronies than their contemporaries. We log-transformed the number of anachronies to satisfy the normality assumptions and fit a linear regression model with the year (centered on 1970) as a predictor to it, and found year to be a significant predictor, however with a poor model fit ($F(1,78) = 16.61$, $p<0.001$, $R^2 = 0.17$). The poor fit is likely because there is a substantial amount of variation throughout the period, and the variation seems to be increasing in time. This indicates also that there may be subtrends in the data – some hidden factor may influence the observed variation for part of the data.

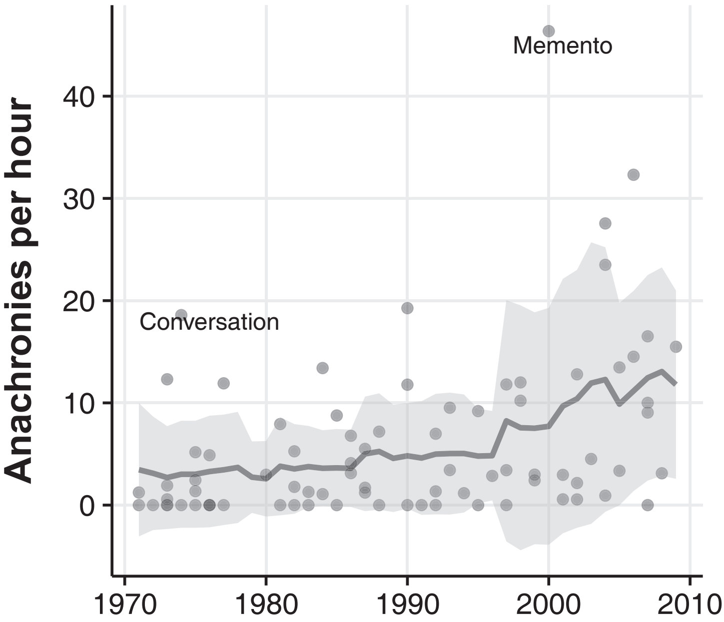
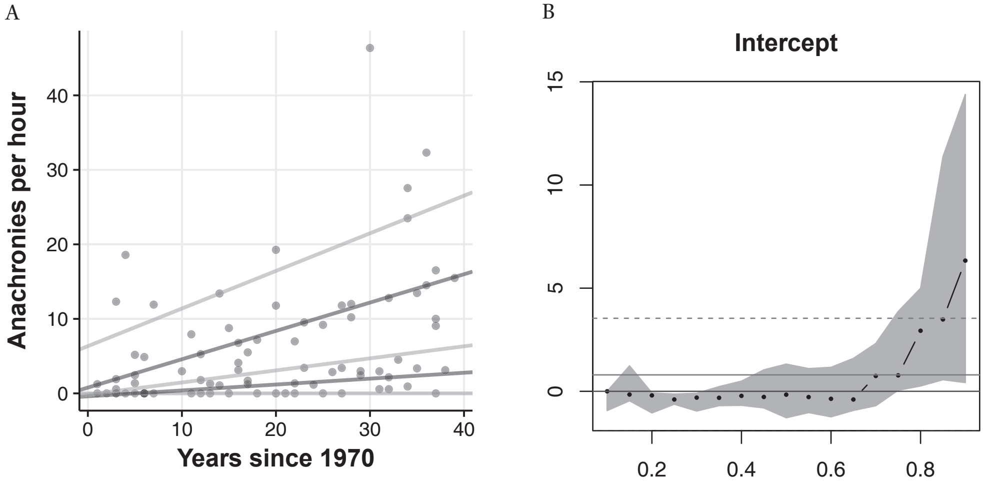


FIGURE 1 The number of anachronies per hour with a rolling mean and standard deviation with a 9-year window.

Since our linear regression did not provide a good model, we applied quantile regression modelling to better understand the heterogeneity in the data. We estimated the slope and intercept for every 5% quantiles between 10% and 90% (Figure 2b–c), and applied a bootstrapping algorithm to estimate the significance of year as a predictor within the 10%, 25%, 50%, 75%, 90% quantiles. We found year to be a significant predictor for the 25th and 75th quantiles (Q25:$t = 2.39$, $p = 0.02$; Q75: $t = 5.09$, $p<0.001$), but not for others. The trendlines are depicted on Figure 2a, with the significant trendlines marked with darker lines. Interestingly, the slope of the regression line is different between the two highlighted models, and, according to the analysis of deviance test ($F(1{,}159) = 5.42$, $p = 0.02$), significantly so. Based on the quantile regression analysis, different parts of the data may have shown different degrees of change during the period. Particularly, the growth of anachronies seems to have influenced more heavily the higher quantiles of the data.

Based on the quantile regression and visual observation of the data we found that the data seem to distribute into three groups in time: 1) films that did not use many anachronies (low intercept, low slope), 2) films that used a moderate amount of anachronies (low intercept, high slope), and 3) films that used many more anachronies than their contemporaries (high intercept,



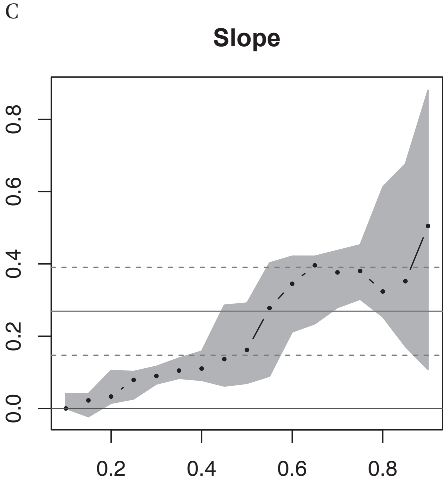


FIGURE 2
Results of the quantile regression analysis.
A: Anachronies per hour regression lines for 0.90, 0.75, 0.50, 0.25, and 0.10 quantile estimates. The 0.75 and 0.25 quantiles with year as a significant predictor are marked with dark grey lines. B: The estimated intercept for the quantile regression models for every 0.05 samples between the reliable extremes 0.10 and 0.90. C: The estimated slope for the quantile regression model for the same samples. For B and C, the grey background shows 95% confidence band for all samples. The horizontal solid lines show the intercept (B) and slope (C) for the ordinary least squares regression with mean as the full line, and 95% confidence intervals as the dotted line.

high slope). While quantile regression is good at finding trends in different quantiles of the data, it can be insensitive to proportional prevalence of particular trends. It may be that particular groups may show quite robust trends. However, if the prevalence of a particular group changes, for example when at some point there are more films in group 1 than usual, quantile regression will distribute these films between the quantiles. If the trend is more characteristic of films in group 1 rather than films with lower rank, then the changes in prevalence will be represented as noise in quantile regression. To capture possibility that there may be diverging types of films with varying prevalence among the most popular films considered in the article, we analysed the dataset also in terms of means for the subgroups.

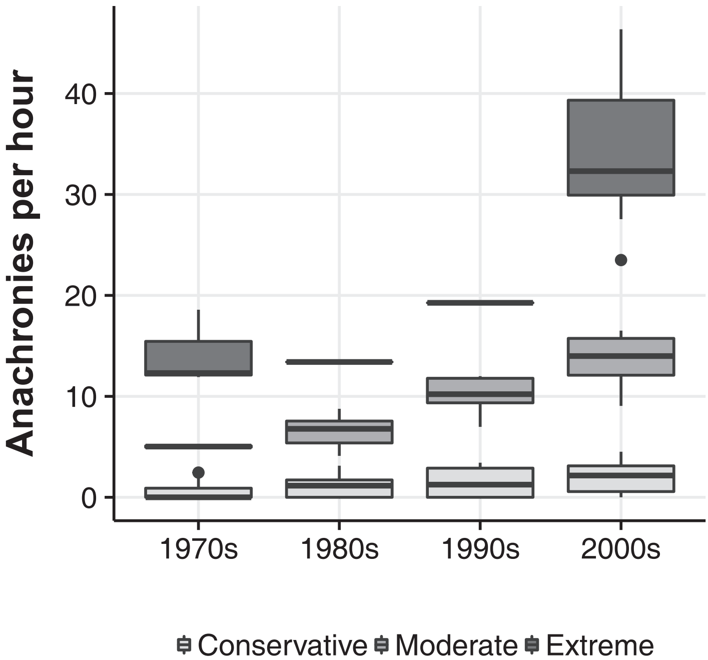


FIGURE 3 Anachronies per hour in each cluster by decade.

To explore this possibility, we classified the data into 3 groups based on the *k*-means clustering algorithm. We did it by running it on each decade separately, and then combining them based on their rank. As a result, we got three clusters spanning across four decades: we can call them conservative, moderate, and extreme groups. As they were now based on the number of anachronies and not their relative rank, the group sizes differed – the clustering algorithm found 48 conservative, 24 moderate, and 8 extreme films in the dataset. The first group showed little to no increase in time, while the latter two showed a noticeable upward trend through the decades (see Figure 3).

We then fit a linear regression model on the clustered dataset – to test whether year and cluster together would predict well the frequency of anachronies. Through model criticism (Baayen, 2008), we excluded 5 films from the model to establish normality (2 from moderate, and 3 from extreme clusters).[2] The resulting model has a very good fit to the data ($F(5,69) = 277.76$, $R^2 = 0.95$) and showed the interaction between year and film cluster to be

2 The films excluded were the biggest outliers in the extreme cluster (*The Last of Sheila* (1973), *The Conversation* (1974), *Memento* (2000)) and borderline cases in the moderate cluster (*Very Long Engagement* (2004) and *Zodiac* (2007)). As a result, the model does not rely on the biggest outliers.

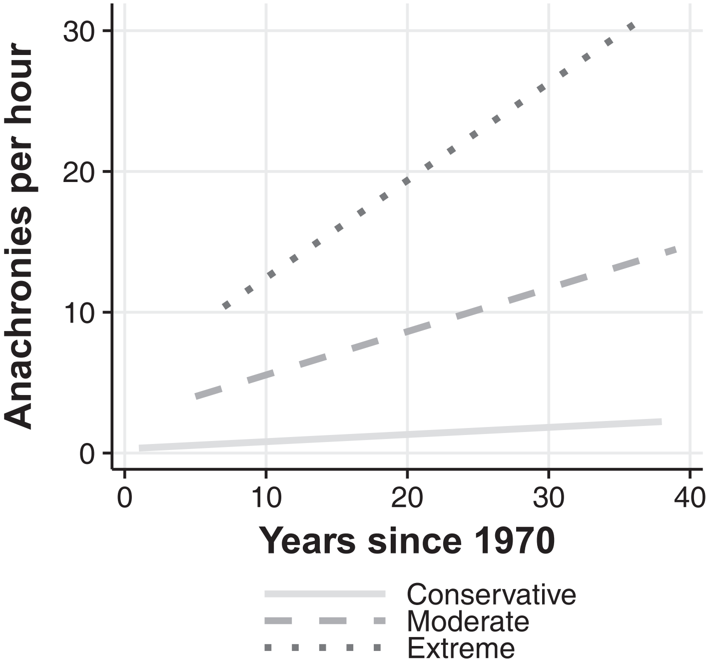


FIGURE 4 Conditional means of the clusters predicted in the regression model with significant interactions between year (centered on 1970) and cluster. Lines: solid – conservative, dashed – moderate, dotted – extreme.

significant (p<0.001 for all pairs), indicating three different slopes for the clusters (see Figure 4). Conservative group showed a very slow increase in the use of anachronies (0.05 an/h per year), the moderate group showed a moderate growth (0.26 an/h per year) and the extreme group showed the highest growth (0.64 an/h per year). The latter trend, however, is the least reliable, as only 5 films from that group are included in the model, and the group itself is likely to consist of outliers. For all groups, there is a reliable increase in the use of anachronies, although it is much more pronounced in moderate and extreme groups.

According to the model, it seems that there were well-describable trends on the frequency of anachronies in films that varied by some unknown variable that determined the type of film (operationalized in the model through clusters). It is possible that the mystery genre encompasses several sub-genres.

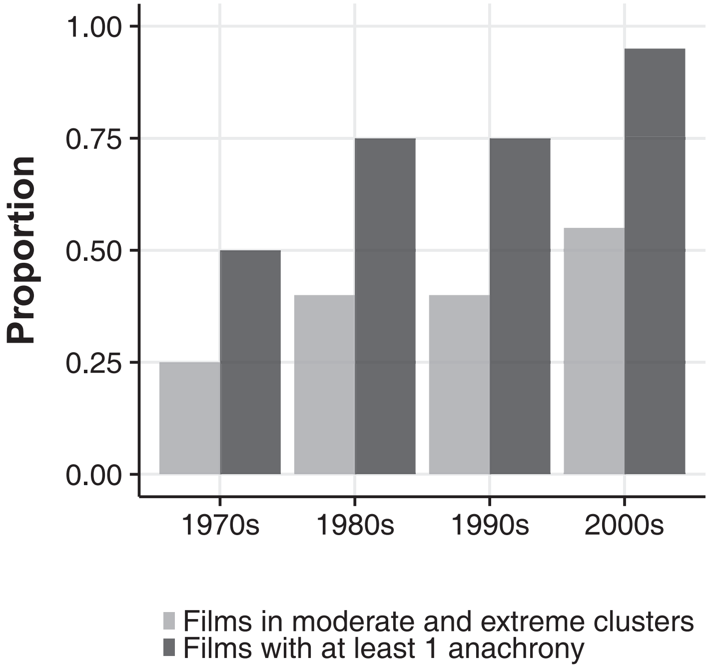


FIGURE 5 The proportion of films that used at least one anachrony (dark grey bars) or made substantial use of anachronies (moderate and extreme clusters, light grey bars) per decade. Each decade has 20 films.

It is interesting to note that, during the observed period, both the proportion of films that used anachronies at least once (the dark grey bars on Figure 5) and the proportion of films that made substantial use of anachronies (the light grey bars on Figure 5) increased. That is, not only the anachronies became more frequent within films (as shown by the model), but there were also more films making use of them (either substantially or at least once).

3.2 *Qualitative Change*

We calculated the cumulative distributions of the relative positions of all anachronies in film time for each of the 59 films that had at least one anachrony. The cumulative distribution shows the proportion of anachronies that have taken place until a particular point in film time – always ranging from 0 to 1. The results for each of the three clusters are depicted in Figure 6, each film is marked with a grey line and the cluster average – with a darker line. Thus, the distribution of anachronies within film time can be seen in the slope

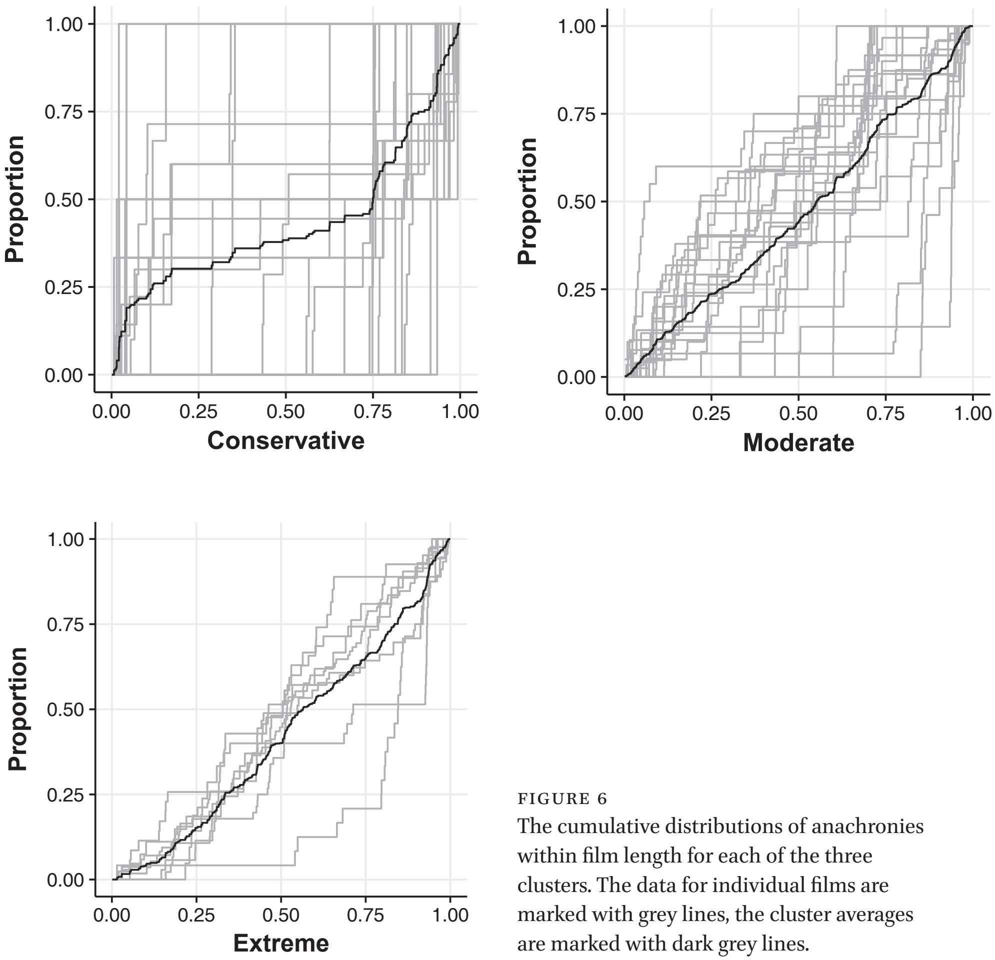


FIGURE 6
The cumulative distributions of anachronies within film length for each of the three clusters. The data for individual films are marked with grey lines, the cluster averages are marked with dark grey lines.

of the lines: the greater the slope between particular points in time, the bigger proportion of anachronies was placed there. The cumulative distributions of anachronies for each film along with basic information can be seen in Table 1 in Supplement A.

Strikingly, the moderate and extreme clusters, on average, show a rather even distribution of anachronies throughout film time, while in the conservative cluster anachronies are mostly placed near the beginning or end of films. Figure 7 plots the proportion of anachronies taking place in the first 5% of the film and last 25% of the film. When considering an aggregate measure of whether an anachrony was in either the first 5% or last 25% of the film, we

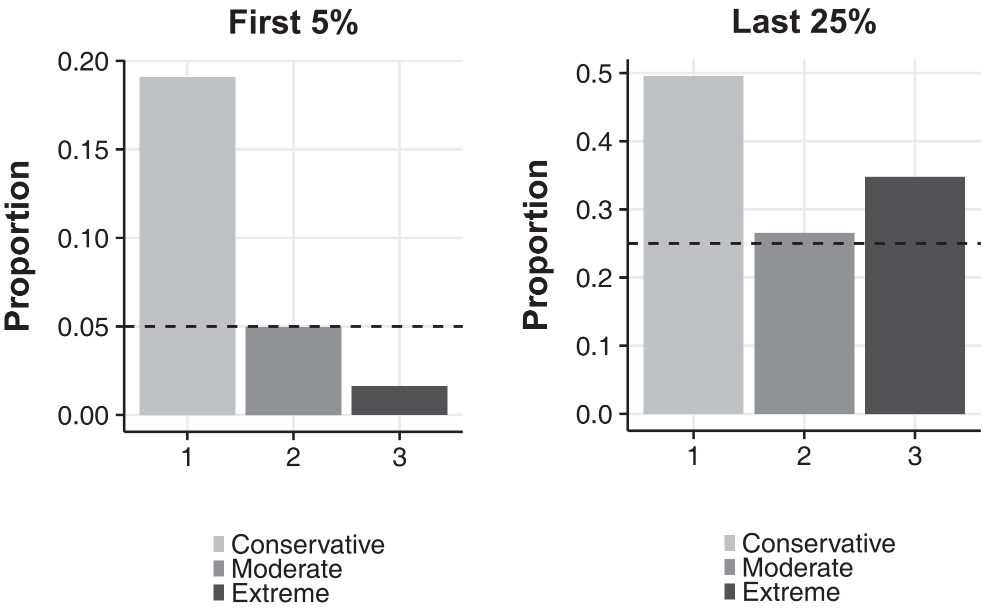


FIGURE 7 The mean proportion of anachronies within films for the first 5% (left) and last 25% (right) of the film duration per cluster. The dotted line shows the expected proportion if anachronies were distributed between films evenly.

find that the conservative group is significantly different from the moderate (U = 535, p<0.001, Cliff's δ = 0.65) and the extreme group (U = 180, p = 0.002, Cliff's δ = 0.67), while the difference between the moderate and extreme group is not significant if the two values are aggregated (U = 76, p = 0.40, Cliff's δ = −0.21). While the extreme group also shows a small preference for the end of the film, both moderate and extreme clusters distribute their anachronies fairly evenly throughout the film. The conservative cluster, on the other hand, shows a clear preference for the beginning and end of the film.

A closer look at the films in three clusters suggests that there may be a functional difference between them. Areas near the beginning and end of a film are special as they are more likely to be used to explain or initiate the plot. For example, in crime films, an anachrony (flashback) is frequently used at the end of film – to show, in retrospect, how exactly the crime was committed. Another typical function of anachronies placed at the beginning or end may be called the "embedding" function. For example, the classic noir movie *Farewell, My Lovely* (1975) consists of two narratives, one embedded into the other. The embedded narrative is presented in a flashback: as a story told by the main hero about his past to a group of listeners. When his long story ends (it is so long that takes most of the film time), we are brought back to the main hero and his listeners – via a flashforward. Therefore, one anachrony – located at the beginning of film – opens the embedded story, and another anachrony – at film's end – closes this story.

The function of anachronies seems to differ in films that have anachronies placed throughout their length (i.e., moderate and extreme clusters). They may be using anachronies as a general technique for evoking viewers' curiosity. For example, *Lucky Number Slevin* (2006) has its anachronies distributed quite evenly, and they can be understood as frequently introduced information gaps in the narrative (same as in *500 Days of Summer*). This function of anachronies may be called the "puzzling" function: in this case, films aim to keep viewers in tension all the time, and that is why they contain multiple anachronies, each of which works as a curiosity trigger.

4 Discussion

In sum, we have found an overall positive trend in the frequency of anachronies in films: during the 1970s–2000s, their number did generally increase. Over time, the number of films that made use of anachronies increased and they did so to a greater degree. However, there also were films that did not make substantial use of anachronies throughout the period. To better understand this heterogeneous data, we used quantile regression and clustering analysis to divide the data into several subgroups. We identified three temporal groups: "conservative", "moderate", and "extreme" films (based on how many anachronies they contain, relative to each other). The clusters of extreme and moderate films showed a noticeable increase in the level of anachronies, during the 1970s–2000s, while the conservative cluster showed virtually no increase. Additionally, there were two other increasing trends in the data: the proportion of films using at least some anachronies has grown, as well as the proportion of anachronies in the moderate and extreme clusters. Thus, we have found support for the quantitative increase hypothesis.

Also, we have found that anachronies are distributed differently within the conservative films, compared to the moderate and extreme films: in conservative films, anachronies are on average concentrated at the *beginning* or the *end* of a film; in other two clusters, anachronies are on average distributed quite *evenly* along the film length. Based on qualitative observations, we argue that this is likely to reflect a difference in function of anachronies. That is, it appears that a qualitatively new function did evolve during the observed period, supporting our qualitative change hypothesis.

Our findings conform to the existing research on cognitive attraction, which indicates that (fairly universal) cognitive preferences of humans can shape cultural artifacts. The theory of cognitive attraction suggests that folklore, visual arts, music, language, and other cultural representations adjust to the cognitive biases of humans. Our study suggests that film evolution can also be described with this theory. Anachronies seem to be an effective technique of evoking human curiosity, and so over time this technique becomes more frequently used. However, what we have found was not a simple linear increase, but a somewhat more complex picture. For some popular films, there is a clear trend to use an increasing amount of anachronies, but for others, this trend is marginal or non-existent: they managed to become popular without using anachronies.

The explanation behind this divergence needs further research into the biases involved in cultural evolution of films. There may be several explanations. One possibility is that some films, despite belonging to the mystery genre, do not aim to cater for our curiosity: they may aim to cater for example our sense of humour or fear. It may also be that there is a wider toolkit of artistic devices that can evoke curiosity without anachronies. Another possible explanation is that the popularity of films is influenced by different kinds of moviegoers, some preferring to have their curiosity aroused by anachronies, others having different preferences.

We expect that our finding could be relevant for film history at large, not only for the mystery genre. Other genres – drama, comedy, horror, etc. – rely on suspense and evoking curiosity as their narrative techniques too, and so we would probably find a similar increasing trend in their use of anachronies. However, these other genres are more likely to offer enjoyment through other means, therefore the expected trend can be less pronounced there; we believe that this trend should be most clearly visible in mystery films, for which suspense arguably is a central technique.

Previous studies on anachronies in film history tended to focus on a small number of films, and when offering explanations to why these films used anachronies, they refer to historical context: e.g., contemporary situation in the Hollywood, or the interest in depicting characters' memory and mental deviations (Buckland, 2009, 2014; Cameron, 2008). Our study offers an alternative explanation: trends in film history may be biased by universal psychological attractors. The fact that the most popular films do seem to form general historical patterns support a universalist explanation to the presence of anachronies.

The story of cultural evolution of anachronies involves more than the films we were able to annotate. It would be particularly interesting to observe how anachronies would be represented in a larger sample of films from this period. Is the trend towards more anachronies typical of all movies, or maybe just characteristic of the most popular ones? Future studies could expand on this general finding by looking at many more films in each year to determine more precisely the mechanisms of cultural reproduction involved: when did the films with anachronies become more popular among the audience? when did the film authors start using anachronies on a large scale? A more detailed dataset would allow a better understanding of the birth and evolution of this artistic device.

Our study further develops the idea that evolution of popular culture can be guided by various cognitive biases proposed by the theory of cognitive attraction. In this paper we suggest that the capacity to evoke curiosity can be an attractor in cultural evolution. With the data that we have, we are unable to test this suggestion against similar explanations. For example, anachronies can make films more memorable, as has been argued in the case of disgust for urban legends (Stubbersfield, Tehrani, & Flynn, 2017), and thus become more prevalent. Or, anachronies can become more prevalent because they increase onscreen visual activity (Cutting, Brunick, DeLong, Iricinschi, & Candan, 2011), and thus can be a technique of capturing viewers' attention.

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Electronic Supplement

Code and data to reproduce the analysis and figures in the paper is available in an Open Science Framework repository: https://dx.doi.org/10.17605/OSF.IO/W3EUM

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