Evolution and Human Behavior 35 (2014) 228–236

Contents lists available at ScienceDirect

Evolution and Human Behavior

journal homepage: www.ehbonline.org

Original Article

Biases in cultural transmission shape the turnover of popular traits

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ARTICLE INFO

Article history:
Initial receipt 17 October 2013
Final revision received 6 February 2014

Keywords:
Cultural evolution
Transmission biases
Neutral model
Turnover
Color terms
Baby names
Musical preferences

ABSTRACT

The neutral model of cultural evolution, which assumes that copying is unbiased, provides precise predictions regarding frequency distributions of traits and the turnover within a popularity-ranked list. Here we study turnover in ranked lists and identify where the turnover departs from neutral model predictions to detect transmission biases in three different domains: color terms usage in English language 20th century books, popularity of early (1880–1930) and recent (1960–2010) USA baby names, and musical preferences of users of the Web site Last.fm. To help characterize the type of transmission bias, we modify the neutral model to include a content-based bias and two context-based biases (conformity and anti-conformity). How these modified models match real data helps us to infer, from population scale observations, when cultural transmission is biased, and, to some extent, what kind of biases are operating at individual level.

1. Introduction

The cultural evolution research program (Boyd & Richerson, 1985; Mesoudi, 2011) has focused on the fact that humans (and, partly, other animals) use various heuristics, referred to as social learning strategies (Laland, 2004; Rendell et al., 2011) or transmission biases (Boyd & Richerson, 1985), to choose when, what, or from whom, to copy. Henrich and McElreath (2003) distinguished between *content-based* biases, where inherent features of the cultural traits at stake determine the choice, and *context-based* biases, where the choice relates instead on features extracted from the social context. For example, Morin (2013) explained the success of direct-gaze portraits over indirect-gaze ones, in painting traditions where both forms are present, with a content-based bias, namely that direct eye-gaze is more cognitive appealing (more attractive, attention-catching, etc.) that indirect eye-gaze. In the case of context-based biases, instead, the choice is not directly determined by the features of the traits, but, for example, by their commonality (conformist bias, Henrich & Boyd, 1998), or by the fact that they are possessed by individuals perceived as more successful or knowledgeable (prestige bias, Henrich & Gil-White, 2001).

The adaptive value of different cultural transmission biases has been elucidated trough theoretical models (see examples in Rendell et al., 2011) and laboratory experiments support in general models' predictions (see examples in Mesoudi, 2009). However, we still miss a full understanding of the impact of transmission biases in real life cultural dynamics (Henrich & Broesch, 2011). In particular, it would be desirable to develop methodologies that allow inferring biases operating at individual level from observed, population scale, frequency patterns (Mesoudi & Lycett, 2009; Shennan, 2011; Kandler & Shennan, 2013). On the one hand, these patterns are the only available information on past cultural traditions, so they are especially relevant for anthropologists and archaeologists (Lycett, 2008; Rogers, Feldman, & Ehrlich, 2009; Shennan, 2011; Kempe, Lycett, & Mesoudi, 2012). On the other hand, these kinds of information are today ubiquitously accessible in form of digitized data, offering an unprecedented opportunity for testing cultural evolutionary hypothesis (Acerbi, Lampos, Garnett, & Bentley, 2013).

In order to identify individual level biases from aggregate, population scale, data, we follow previous works that studied departures from the predictions of models of cultural evolution that assume that social learning is completely unbiased, that is, individuals choose at random from whom to copy (Mesoudi & Lycett, 2009; Shennan, 2011; Acerbi, Ghirlanda, & Enquist, 2012; Kandler & Shennan, 2013). This class of models – known as "neutral" or "random copying" models (Neiman, 1995; Bentley, Hahn, & Shennan, 2004; Lieberman, Hauert, & Nowak, 2005) – provide detailed predictions on the expected outcomes of the cultural evolutionary process, and have been shown able to account for empirical regularities observed in cultural domains as diverse as decoration patterns in Neolithic pottery (Neiman, 1995), popularity of first names (Hahn & Bentley, 2003) or dog breeds (Herzog, Bentley, & Hahn, 2004, see also Ghirlanda, Acerbi, Herzog, & Serpell, 2013), and usage of keywords in academic publications (Bentley, 2008).

Mesoudi and Lycett (2009) added biases to the neutral model and examined through computer simulations how they may impact the

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1090-5138/$ – see front matter
http://dx.doi.org/10.1016/j.evolhumbehav.2014.02.003

frequency distribution of cultural traits. The neutral model produces characteristic right-skewed distributions, where very few traits are very popular, and the vast majority of traits remain rare. Conformity, Mesoudi and Lycett (2009) showed, produces "winner-take-all" distributions, which are even more skewed than the ones produced by neutral models, since popular traits are proportionally more advantaged. Anti-conformity, or negative frequency-dependent copying (a bias against popular traits), produces instead distributions where the majority of traits result at intermediate frequencies.

Others concentrated on the change through time of frequencies, comparing empirical data with model results. Kandler and Shennan (2013) used the probability of the observed number of cultural variants present in a population as another diagnostic prediction of the neutral model that could be readily compared to real data, and they showed that discrepancies with neutral model predictions suggested the presence of context-based, frequency-dependent biases in decoration of pottery in early Neolithic Europe. Steele, Glatz, and Kandler (2010) did not find significant differences between neutral model predictions and data regarding frequency distributions, but they showed the existence of a correlation between functional characteristic of the traits studied (Bronze Age vessels) and their abundance, which may be a signature of a content-based bias.

In this paper, we focus on departures from a different set of predictions of the neutral model, namely predictions on the turnover of cultural traits. Popular examples of turnover are widespread information on "new entries" in various top charts (Top 5, Top 40, etc.), a ubiquitous feature in contemporary culture. However, it is possible to calculate the turnover for any cultural domain – examples include frequency of pottery designs (Bentley et al., 2004), word usage (Bentley, 2008), or bird song elements (Byers, Belinsky, & Bentley, 2010) – knowing the frequencies through time of different cultural traits.

We define turnover, for a list of cultural traits ranked in order of abundance of size y, the number z of new traits that enter in that list at each time step considered. For example, the turnover of recent females baby names in USA is around 1 for a top list of size 10 (Bentley, Lipo, Herzog, & Hahn, 2007), meaning that, every year, on average, one new name enters in the Top 10. Measuring turnover for different sizes of top lists indicates where exactly change happens. For example, If turnover is rapid for large top lists (e.g. Top 100 or Top 1,000) and this contrasts with comparatively slow turnover for small list sizes (e.g. Top 5), this may indicate a bias toward popular traits.

Although it may appear simple, turnover in top lists in neutral evolution is a highly challenging analytical problem (Eriksson, Jansson, & Sjöstrnad, 2010). In order to make meaningful interpretations from turnover, we use the neutral model as our null model. Using simulations, Bentley et al. (2007) found that the turnover yielded by the neutral model was close to data from various cultural domains, such as Top-100 record charts, first names, and popularity through time of dog breeds in USA, and proposed a simple rule of thumb, by which $z = y\sqrt{\mu}$, where z is the average turnover of variants in the top list of size y, and μ is the innovation rate. We will refer to the function that transform the ranked list's size y in the turnover z as 'turnover profile'.

Subsequently, Evans and Giometto (2011) extended and improved the conjecture of Bentley et al. (2007), confirming that the turnover profile for the neutral model may be indeed considered approximately linear. However, they showed that, in general, turnover can be more precisely described by:

$$z = d \cdot \mu^a \cdot y^b \cdot N \tag{1}$$

where N is the population size, and d, a, b, c vary for different parameter combinations. Simplifying Evans and Giometto (2011) formula, it is possible to describe the turnover profile for a large area of the parameter space with a generic function:

$$z = a \cdot y^b \tag{2}$$

with a encompassing all the other variables in the full equation of Evans and Giometto (2011), and, in the case of neutral model, $b = 0.86$. Importantly, the value of b determines the shape of the function that describes the turnover profile, with $b \approx 1$ describing a linear relation between z and y (as in the rule of thumb conjectured by Bentley et al., 2007).

Here we use this formula to describe the turnover profile of three cultural domains, namely color terms usage in English language 20th century books, popularity of early (1880–1930) and recent (1960–2010) USA baby names, and musical preferences of users of the website Last.fm, showing when the turnover profile differs from neutral model predictions.

Then, we follow previous work (Mesoudi & Lycett, 2009) in introducing, with small modifications, three transmission biases to the neutral model, and observing turnover in the resulting simulated popularity distributions. In the first model ("Attraction model"), transmission is content-biased, i.e. some traits are favored in respect to others since they are more "attractive" because of their intrinsic features (Claidière & Sperber, 2007; Morin, 2013). The second and the third are context-based biases: conformity, where transmission is positively frequency-biased (i.e. the popular traits are preferred in respect to the unpopular ones), and anti-conformity, where transmission is negatively frequency-biased (i.e. the unpopular traits are preferred in respect to the popular).

The turnovers yielded by these models differ from neutral model predictions in a consistent way. Content bias and conformist bias produce 'convex' turnover profiles, indicating that popular traits change slower than what would be expected under neutral model assumptions. On the contrary, an anti-conformist bias in cultural transmission produces a 'concave' turnover, where popular traits change faster than what would be expected. The models' turnovers reproduce the profiles found in the cultural domains examined, allowing us to infer, from population level data, when cultural transmission is biased, and, to some extent, what kind of biases are operating.

2. Turnover in empirical data

2.1. Methods

2.1.1. Color terms

Universals in color naming have a long history in anthropology and linguistic. Berlin and Kay (1969) proposed that the basic color terms of a language could be predicted if one knows how many color terms are present in that language. For example, if a language has two color terms, they will be approximately indicating 'dark/cool' and 'light/warm' (somewhat analogous, but wider, than English language 'black' and 'white'); if a languages has three terms, 'red' will be added, and so on. Recent researches have shown through computational models (Baronchelli, Gong, Puglisi, & Loreto, 2010; Loreto, Mukherjee, & Tria, 2012), or iterated learning experiments (Xu, Dowman, & Griffiths, 2013), that weak cognitive constraints, coupled with cultural transmission process, can indeed produce a hierarchically structured, and regular, color taxonomy.

Taking advantage of a possible cultural universal, we are interested to check if this might reflect in the usage of color terms in books (see also Dehaene & Mehler, 1992) and has an effect on their turnover. We looked for the number of time color terms are used in the Google Books Ngram corpus (Michel et al., 2011), which, in the latest available version (July 2012), contains over 8 millions books (Lin et al., 2012). We consider only English language books (the language with