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 website 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, 1988; 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, 1988), to choose when, what, or from whom, to copy. Henrich & 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 (Kandler & Shennan, 2013; Mesoudi & Lycett, 2009; Shennan, 2011). On the one hand, these patterns are the only available information on past cultural traditions, so they are especially relevant for anthropologists and archaeologists (Kempe et al., 2012; Lycett, 2008; Rogers et al., 2009; Shennan, 2011). 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 et al., 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 (Acerbi et al., 2012; Kandler & Shennan, 2013; Mesoudi & Lycett, 2009; Shennan, 2011). This class of models — known as "neutral" or "random copying" models (Bentley et al., 2004; Lieberman et al., 2005; Neiman, 1995) — 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 et al., 2004, see also Ghirlanda et al., 2013), and usage of keywords in academic publications (Bentley, 2008).

Mesoudi & Lycett (2009) added biases to the neutral model and examined through computer simulations how they may impact the 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 & 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 & 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 et al. (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 et al., 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 et al., 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 et al., 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 & 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:

$$z = d \cdot \mu^a \cdot y^b \cdot N^c \qquad (1)$$

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

$$z = a \cdot y^b \qquad (2)$$

with *a* encompassing all the other variables in the full equation of Evans & 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 & 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 et al., 2012; Loreto et al., 2012), or iterated learning experiments (Xu et al., 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 the biggest sample size) from 1900 to 2000, for a total of 2,980,271 volumes. The Ngram database gives information on how many times, in a given year, an 1-gram or an n-gram is used, where a 1-gram is a string of characters uninterrupted by space (generally a word, but also numbers, typos, etc.) and an n-gram is a sequence of *n* 1-grams.

Basic color terms were retrieved from the “Simple English” version of Wikipedia (from http://simple.wikipedia.org/wiki/List of colors). Bi-grams (e.g. ‘Electric blue’) and terms which main referent was likely not to be the color (e.g. ‘Chocolate’, ‘Gold’) were excluded, leaving a total of 61 1-grams. For each 1-gram we collected the yearly occurrences (case insensitive). Since the number of books varies considerably through years, we normalized the count of 1-grams using the yearly occurrences of the word ‘the’ (as in Acerbi et al., 2013, notice however that normalization does not affect the turnover but it is used only for visualizing the trends through time). For each year we ranked the color terms according to their popularity, and calculated the average turnover profile on 100 years for the most popular 30 elements. The data were then fitted with the generic function for the turnover profile (equation 2), and with the same function, but assuming unbiased copying (b = 0.86):

$$z = a \cdot y^{0.86} \qquad (3)$$

2.1.2 Baby names

Bentley et al. (2007) found that USA baby names exhibited an approximately linear turnover profile that was consistent with their neutral model predictions. However, they also found a difference between female and male baby names, namely that the slope of turnover of female names was higher, corresponding to the well-known finding that there is more innovation in naming girls than boys (Lieberson, 2000; Hahn & Bentley, 2003; Bentley et al., 2007; Gureckis & Goldstone, 2009). Another interesting trend in baby names popularity is that preferences, over time, shifted toward more novel names, becoming less uniform (Lieberson, 2000). In 1950, for example, the 76% of newborn males were given one of the 100 most popular names, while today the percentage fell down to 43%.

Taking into account these facts, we divided the data collected from the Social Security Administration of the USA (from http://www.ssa.gov/OACT/babynames/) in early (first 50 years of records: 1880 to 1930) and recent (last 50 years of records: 1960 to 2010) periods, and also separated male and female names. For each dataset, we ranked the names according to their yearly popularity, and we calculated the average turnover on 50 years for the most popular 30 elements, analogously to the color terms data. As described above, we then fitted the turnover profile of the four datasets (early males, recent males, early females, recent females) with the generic function (equation 2) and with the unbiased-copying function (equation 3).

2.1.3 Musical preferences

Last.fm (http://www.last.fm) is a music website that offers several social networking functionalities. Last.fm builds a profile of registered users (while there is not an official statistics, the count of users is estimated to be around 40 million), integrating information provided by the users with data about the songs that they listen to in their devices, on various internet-radios, or on the Last.fm own radio. An interesting feature of the website is that users can create and join “groups” related to various common interests. Groups may be linked to particular countries (‘Nederlanders!’), musical tastes (‘Female fronted Metal’), artists (‘Queen’), or more generic labels (‘Addicted to Last.fm’).

We used Last.fm official APIs (http://www.last.fm/api) to track the ‘weekly artist chart’ (i.e. the 100 most listened artists in a group) for 52 consecutive weeks (starting from 14 September 2012) for a sample of 30 groups defined by specific musical genres (e.g. ‘Acid Jazz’, ‘BLUES!’, ‘80s Gothic Metal’), and for a sample of 30 “generalist” groups (groups related to countries or generic labels, e.g. ‘Indonesia’, ‘Music Is My Girlfriend’, ‘I Hate Music Snobs’). We choose groups with more than N = 3,000 members (for “genre-based” groups: average N = 7,195. For “generalist” groups: average N = 8,998) that were present in the ‘Recently Active Groups’ page (http://www.last.fm/community/groups/active) when starting the data collection. In Electronic Supplementary Materials, we provide the complete list of the groups we used in the analysis, and their size. We finally calculated the average turnover profile on 52 weeks for the most popular 30 elements in each group.

In this domain, we were interested to compare how the turnover profiles varied between the two different samples, expecting members of “genre-based” groups, differently from members of “generalists” groups, to be biased toward a subset of artists. We thus fitted the 60 turnover profiles with the generic function (equation 2) to find their b values, and measured the dissimilarity between the two samples.

2.2 Results

2.2.1 Color terms

Figure 1 shows the frequency, normalized with the yearly count of occurrences of the word ‘the’, through the 20th century, of the most used 8 color terms: ‘white’, ‘black’, ‘red’, ‘green’, ‘blue’, ‘brown’, ‘yellow’, and ‘gray’ (as it is spelled in Wikipedia). First, it is interesting to point out the resemblance with the original taxonomy proposed by Berlin & Kay (1969), with the only main difference that the color term 'yellow' is less frequent than what would be expected. Second, it is worth to notice that the term 'black' roughly double the frequency from 1960 to 2000, in concert with Civil Rights Movement (Smith, 1992).

From Fig. 1 one can infer that color terms show a consistent stability in their usage in books through time. We used Akaike's Information Criterion (AIC) to compare the relative likelihood of the two functions to describe turnover profile (Fig.2). The generic function (equation 2) has a lower AIC, and its Akaike's weight (i.e. the relative probability of being correct, in respect to the alternative function that assumes unbiased copying - Burnham & Anderson, 2002) is $\omega = 0.999$. The best fitting of the generic function has an exponent of $b = 1.88$. This suggests that the cultural dynamics underlying the usage of color terms in English 20th century books might not be best described as an unbiased copy process.

2.2.3 Baby names

In three out of the four cases we took in consideration, early male names, and recent male and female names, the generic function fits better the data than the alternative unbiased- copying function (Fig. 3). In detail, the generic function's fit of the turnover profile of USA male baby names from 1880 to 1930 has an Akaike's weight of ω = 0.999 and an exponent of $b = 1.69$, while, from 1960 to 2010, these values are ω = 0.999 and $b = 0.51$. For female names, the fit of early (1880 to 1930) names turnover results in $\omega = 0.485$ and $b = 0.81$, while for recent (1960 to 2010) female names the values are $\omega = 0.999$ and $b = 0.56$.

The turnover profile of early male baby names (Fig. 3 Top-left), analogously to the above reported turnover of color terms in English books (Fig. 2), has an exponent $b > 0.86$, which indicates that popular items change (relatively) slower than less popular items. On the contrary, the turnovers of recent baby names (both females and males, Fig. 3 Right panels) have an exponent $b < 0.86$, meaning that popular names change relatively faster than less popular names. In the case of early female baby names (Fig.3 Bottom-left), the fit of the turnover profile does not allow to distinguish between the two alternative functions.

2.2.3 Musical preferences

Values of b obtained for "genre-based" groups (1.06 ± 0.23, $N = 30$) were significantly higher (two samples t test, $t_{56} = 3.64$, $P < 0.001$) than the values for "generalist" groups (0.85 ± 0.19, $N = 30$), indicating that popular artists tend to be more stable in the top positions of "genre-based" groups' charts than in "generalist" groups' charts (Fig.4). Interestingly, the average value of b for "generalist" groups is almost exactly the value predicted by the neutral model turnover profile. In Electronic Supplementary Materials, we provide the data of the values of b for all 60 groups considered.

3. Models

3.1. Methods

3.1.1 Neutral model

We first reproduced the neutral model of cultural evolution described in Bentley et al. (2004). We consider a population of N individuals, each with a single cultural trait. At the beginning, each individual has a different cultural trait. The model runs in discrete time steps. At each time step, all individuals are simultaneously assigned a new cultural trait. With a small probability μ, an individual will introduce a new cultural trait. The remaining individuals ($1-\mu$) copy the cultural trait from a randomly selected individual of the previous generation.

We run the model until reaching a steady state (for $\tau = 4\mu$–1 time steps) and after that we calculate the turnover, averaging it on $T = 50 + \mu$–1 time steps (values for τ and T are extracted from Evans & Giometto, 2011). We study the turnover for top list sizes (y) from 10 to 100 (with a step of $y = 1$) and for population from 200 to 10,000 individuals (with a step of $N = 200$). Finally, for all parameters, we consider three values of the probability of innovation (μ): 0.005; 0.01; 0.02.

3.1.2 Attraction model

In the neutral model, transmission is unbiased: the $(1 - \mu)$ proportion of individuals who copy choose randomly from whom to copy, and copy independently of any consideration on the cultural trait they possess. We implemented content-biased transmission by assigning to each cultural trait i a value α_i (attractiveness), randomly extracted from a standard normal distribution (i.e. with mean 0 and standard deviation 1), meaning that the majority of traits will have intermediate values of $\alpha \approx 0$, while few traits will be particularly attractive, and few will be particularly unattractive.

As in the neutral model, the $(1-\mu)$ individuals who copy pick up randomly an individual from the previous time step, but their decision whether to copy or not may depend on the attractiveness of their traits. A parameter C determines, for each copying event, the probability that transmission will be content-biased. At each time step, a fraction of $C(1-\mu)$ individuals (on average) only copy if their own trait "is not attractive enough". This is implemented by having individuals compare the attractiveness of the trait i they already bear with the attractiveness of a trait j randomly extracted in the population, such that an individual copies another individual's trait only if $\alpha_{j\cdot} > \alpha_{i\cdot}$ The remaining fraction of individuals $(1 - C)(1 - \mu)$ copy unconditionally as in the standard neutral model.

Simulations are run in the same conditions described above for the neutral model, and three values of the parameter *C* are tested: 0.1; 0.5; 0.9.

<u>3.1.3 Conformist model</u>

We implement frequency–dependent biases by giving to individuals information on which traits are present in a “top list” of size 10 (following Mesoudi & Lycett, 2009, where conformist individuals adopt the top 1 trait in the population). Analogously to the attraction model, in the conformist model the parameter *C* determines the probability of a copying event being biased. In the conformist (positive frequency-dependent) model, a fraction of $C(1 - \mu)$ individuals “know” whether or not the trait they bear is one of the 10 most popular traits in the population. If it is, they do not copy, while if not in the top 10, then they go ahead and copies another individual’s variant. In other words, the $C(1 - \mu)$ conformist individuals copy only if the trait they bear is not popular. Simulations are run as described above, with the same *C* values reported for the attraction model (0.1; 0.5; 0.9).

<u>3.1.4 Anti-conformist model</u>

As above, a fraction of $C(1 - \mu)$ individuals has an information on whether or not the trait they bear is one of the most 10 popular traits in the population. In the anti-conformist (negative frequency-dependent) model, however, they copy only if the trait they bear is among the 10 most popular traits in the population, i.e. they will get rid of their traits if they are popular. Simulations are run as described above.
A Matlab code to reproduce all the models is provided in Electronic Supplementary Materials.

3.2 Results

The neutral model reproduces the results reported in Bentley et al. (2007) and Evans & Giometto (2011). While the turnover profile appears approximately linear (see example in Fig. 5 Top-left, $N = 5{,}000$; $\mu = 0.01$), the extended analysis of different parameters (following Evans & Giometto, 2011), suggests indeed that in a wide area of the parameter space the turnover yielded by the neutral model is better described by an exponential function. We fitted the turnover of the simulated data with the generic function (equation 2) and we found that, in most cases, the exponent b is lower than 1 (Fig. 6 Top-left). This result is consistent with the results of Evans & Giometto (2011), that, as discussed above, found an overall best fit of $b = 0.86$ in their simulations. In Figure 1 ESM (Electronic Supplementary Materials) we additionally show that indeed the generic function (equation 2, with b free to vary) does not fit the simulated data better than the neutral model theoretical expectations (equation 3, $b = 0.86$), confirming that simulated turnover profiles are consistent with random copying.

In Fig. 6, the white space represents an area of the parameter space where the total number of traits in the population (S), at equilibrium, is lower than the size of the top list on which the turnover is calculated (y), so that is not possible to calculate the turnover. In the case of the neutral model, this corresponds to the limit found by Evans & Giometto (2011) of $N\mu < 0.15y$.

Both the attraction and the conformist model yield instead a ‘convex’ turnover (see example in Fig. 5 Top-right and Bottom-left, $N = 5{,}000$; $\mu = 0.01$; $C = 0.5$), where popular traits change relatively slower than unpopular ones. The extended analysis of the parameter space (Fig.6 Top-right and Bottom-left) confirms that b is consistently higher than 0.86. Content-biased copying and, especially, positive frequency-dependent biased copying also produce a lower number of traits at equilibrium in respect to the neutral model, which results in a wider area of the parameter space where is not possible to calculate the turnover (i.e. the white space in Fig. 6). This is due to the fact that, in both cases, a subset of few traits is favored in respect to the others (in the attraction model because they are 'intrinsically' better, and in the case of the conformist model because, for random reasons, they became more popular).

Finally, an anti-conformist bias produces a 'concave' turnover (see example in Fig. 5 Bottom-right, $N = 5{,}000$; $\mu = 0.01$; $C = 0.5$), where popular traits change more rapidly than what would be expected under the hypothesis of unbiased copying. Again, extending the analysis to different population sizes and various sizes of the top lists (Fig.6 Bottom-right) confirms that, in all parameter space, the fitted exponent b is constantly lower than 0.86. The space in which was not possible to calculate the turnover ($S < y$, i.e. the white space in Fig. 6) is here more limited in respect to the neutral case, because a negative frequency-dependent bias tends to favor proportionally low-frequency traits, increasing the total number of cultural traits S in the population.

Results with higher ($\mu = 0.02$) and lower ($\mu = 0.005$) innovation rates are consistent with this general picture for the four models, and they are not reported here.

4. Discussion

Using a simple formula to describe the turnover profile of a given cultural domain, we have shown that the turnover of color terms in English books of the 20th century, early and recent male names, recent female names, and artists success in "genre-based" Last.fm users groups deviates from neutral model predictions, suggesting the presence of some form of cultural selection. On the contrary, the turnover of early female names and popularity of artists in "generalist" Last.fm users groups cannot be distinguished by the one produced by an unbiased-copying process.

Modifications of the neutral model show that, by introducing biases in cultural transmission, it is possible to reproduce the diagnostic features of the turnover profiles we studied in empirical data. In particular, we focused on the shape of the turnover profile (determined by the value of the exponent *b* in equation 2). The main result is that biases that select popular traits produce ‘convex’ turnover profiles, where *b* is consistently higher than neutral model predictions ($b = 0.86$), while biases that favor unpopular traits produce ‘concave’ turnover profile, and an exponent *b* consistently lower then the one produced by unbiased copying.

Comparing empirical data with models outcomes, for color terms in English books of the 20^{th} century, the turnover is described by a convex function, that indicates that positive selection acts on the most popular traits, and is then relaxed for less popular, reflecting the existence of individual level biases towards a subset of colors. In the case of baby names, we can distinguish the case of early boys names, where we find again a convex function; early girls names, where the turnover profile is undistinguishable from neutral model; and recent names, where for both males and females the function is concave. This corresponds to the well-known facts that name popularity became less uniform over time and that there is more innovation in girls names than in boys names. The turnover of recent names indicates indeed that popular names are negatively selected, i.e. they change more than what would be expected, both for males and females. Negative selection is relaxed, for girl names, in early years, while for boy names there is an opposite effect, with popular name positively selected. Finally, in the case of musical preferences, we have shown that it is possible to identify users groups that are more or less biased towards a subset of specific artists by comparing the values of *b* that better describe their turnover profile, with higher values of *b* indicating that the preference for some artists is stable in certain users groups (as it happens in the case of the "genre-based" groups that we analyzed).

While recent names turnover is an example of anti-conformism, or negative frequency dependent bias, we cannot distinguish, with this results, between cultural attraction and conformist bias in the other cases, because they all produce the same effect of increased selection of popular traits. It reasonable however to assume that, for the empirical case we examined, the 'convex' turnover of color terms popularity is a result of content bias, while for early boys names and musical preferences in Last.fm "genre-based" groups a conformist bias is likely to act. The dynamics and the conditions where one would expect context or content biases being predominant in cultural evolution have received some attention (Claidière & Sperber, 2007; Henrich & Boyd, 2002; Morin, 2011, Walters & Kendal 2013) but we still need more research in order to be able to understand, starting from population level data, the exact biases involved in cultural change.

Although different implementations of the models can change the details of the results (for example different proportion of attractive versus non-attractive traits, or different copying mechanisms, e.g. individuals evaluating explicitly the observed traits instead of their own), the general relation between the shape of the turnover profile and the underlying transmission bias is likely to be independent from these differences. Also, our implementation of the frequency-dependent biases (both conformist and anti-conformist bias), based on individuals having information on a "top list" of cultural items, may seem at odds with the more common strategy used in the cultural evolution literature. In general (see for example Henrich & Boyd, 1998), conformist bias is modeled by having individuals copying common traits with a probability higher than traits' frequency. As a variation on standard conventions in modeling conformist bias, our "top list" implementation seems an appropriate assumption about individuals' knowledge of popularity levels in a population (see Eriksson et al., 2007 for discussion). Additionally, it is a computationally efficient means to model conformity, consistent with prior models, as an extension of assumptions that individuals copy the most popular trait (Mesoudi & Lycett, 2009). In any case, different implementations (a more standard — explicitly frequency-dependent — bias, or different values of *N* in the top *N*) may again change the details of our results (e.g. the bend in the turnover profile will occur at rank *N*) but not the general conclusion. Regarding this last point, frequency-dependent biases produce, in fact, in our model, a turnover profile possibly described by two distinct linear functions (see examples in Fig. 5 Bottom). However, we decided to focus on the more general 'concavity' or 'convexity' of the profile to compare with the empirical data, as we believe that such a strong effect might be obscured by other factors in real cultural dynamics. On the other side, an interesting possibility would be to check on which degree empirical turnover profiles could be described by two linear functions, as a sign of a possible effect on cultural evolution of the ubiquitous presence of public "top N" lists.

Another promising extension of our model would be to analyze outcomes for more realistic conditions involving bigger population sizes, or, possibly, for population sizes changing in time. Simulating larger population ($N > 10{,}000$) is however computationally demanding. Evans and Giometto (2011) showed that, in any case, the dependence of the turnover profile on N is not strong. They found for equation (1) a value of the exponent $c = 0.09$, meaning that, for example, a tenfold increase in N should increase the turnover z only by a factor of about 1.2.

Similarly, we assumed that individuals could copy cultural traits only from the previous generation, while in reality – say, in the first names case – one is free to pick up traits from virtually all past generations, as long as the information is preserved. Bentley et al. (2011) explored this possibility by introducing a “memory parameter” in the neutral model, allowing individuals to look at more than one previous generation. They showed, in respect to the turnover profile, that increasing memory reduces the effect of the innovation rate, but further studies are needed to understand how memory could impact on the “shape” of the turnover profile, as the introduction of specific transmission biases does.

Many recent works analyzed departures from neutral model (a review is Shennan, 2011), however this work is to our knowledge the first analysis showing that popularity turnover may be a strong indicator of the presence of cultural selection. Of course, we deliberately choose cultural domains where we suspected the presence of transmission biases, but similar analyses can be used in general on population level data, and being especially meaningful where one does not know whether forms of cultural selection are acting.

This seems especially important today, since a new level of accessibility as well as volume of data concerning human behavior might transform the study of cultural evolution. Most of those data, however, are more easily tractable, or even only accessible, in the form of aggregate, population-level, information. Methods allowing inferring individual behaviors from aggregate data and, particularly, to connect this massive amount of information to well established theories can be a valuable contribution to the study of cultural evolution.

We also believe that out “top list”-based implementation of frequency-dependent biases could be seen as computationally equivalent to the mechanism embedded within demographic models of cumulative knowledge, in which each individual effectively learns from the most skilled individual (prestige bias), even among a population of thousands (Henrich 2004, 2006; Powell et al. 2009). In taking this forward, we might also hypothesize that this cognitive bias towards copying the "best" – most popular or most skilled – is exploited and distorted in the modern era, when digital technology actually makes it possible to copy using information at global level, no matter how large the population size.

Acknowledgments

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Figure legends

Figure 1. Color terms usage frequencies in 20th century English books. Line colors represent the actual color terms. Values are smoothed using Friedmans 'super smoother' through R function supsmu().

Figure 2. Turnover in popularity usage of color terms in 20th century English books. The continuous and dotted lines represent respectively the best fit according to the generic function (equation 2) and a fit assuming unbiased copying (b = 0.86).

Figure 3. Turnover in popularity of USA baby names. The continuous and dotted lines represent respectively the best fit according to the generic function (equation 2) and a fit assuming unbiased copying (b = 0.86). Top-left: male baby names from 1880 to 1930. Top-right: male baby names from 1960 to 2010. Bottom-left: female baby names from 1880 to 1930. Bottom-right: female baby names from 1960 to 2010.

Figure 4. Values of the exponent *b* of the turnover profile in the artists weekly chart for 30 "generalists" and 30 "genre-based" groups of Last.fm users. Boxes represent the interquartile range of the data. The horizontal lines inside the boxes indicate the mean values. The horizontal lines outside the boxes indicate the minimum and maximum values. The dotted line is the prediction assuming unbiased copying.

Figure 5. Examples of turnover in simulated data. Top-left: neutral model. Top-right: attraction model. Bottom-left: conformist model (positive frequency-dependent). Bottom- right: anti-conformist model (negative frequency-dependent). N (population size) = 5,000, μ (innovation rate) = 0.01. For the biased transmission models, C =

0.5. All data are averaged on 100 simulation runs.

Figure 6. Values of the exponent *b* of the turnover fit in simulated data. Top-left: neutral model. Top-right: attraction model. Bottom-left: conformist model (positive frequency- dependent). Bottom-right: anti-conformist model (negative frequency-dependent). In all cases, μ (innovation rate) = 0.01. For the biased transmission models, $C = 0.5$. The white area in the plots represents the area of the parameter space where the total number of traits at steady state was minor than the size of the top list on which turnover was calculated ($S < y$). Notice that, for the conformist and anti-conformist model, y (the size of the top list on which the turnover was calculated) starts at 20, since for lower values some fits were ill conditioned. All data are averaged on 100 simulation runs.

Figure 1

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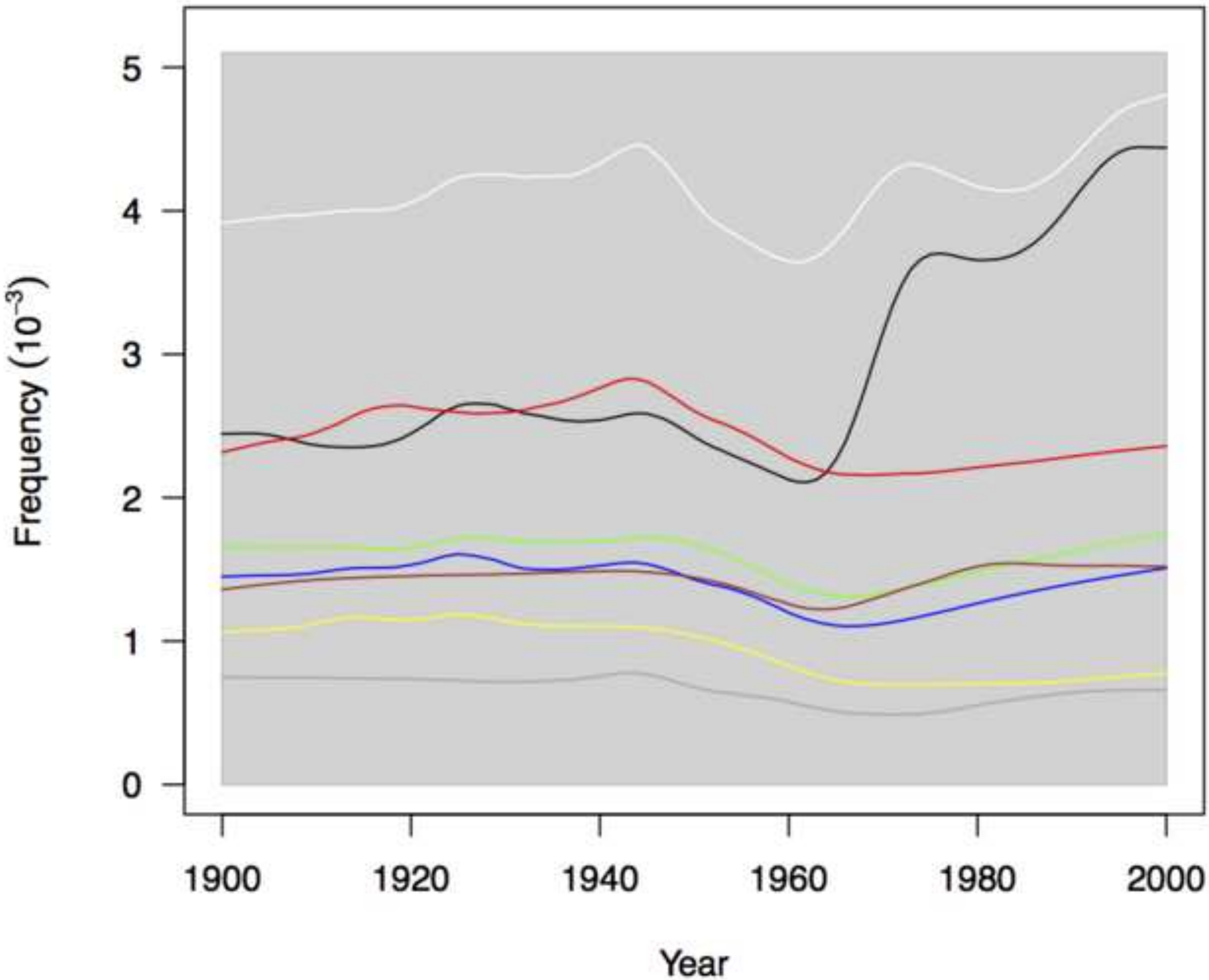

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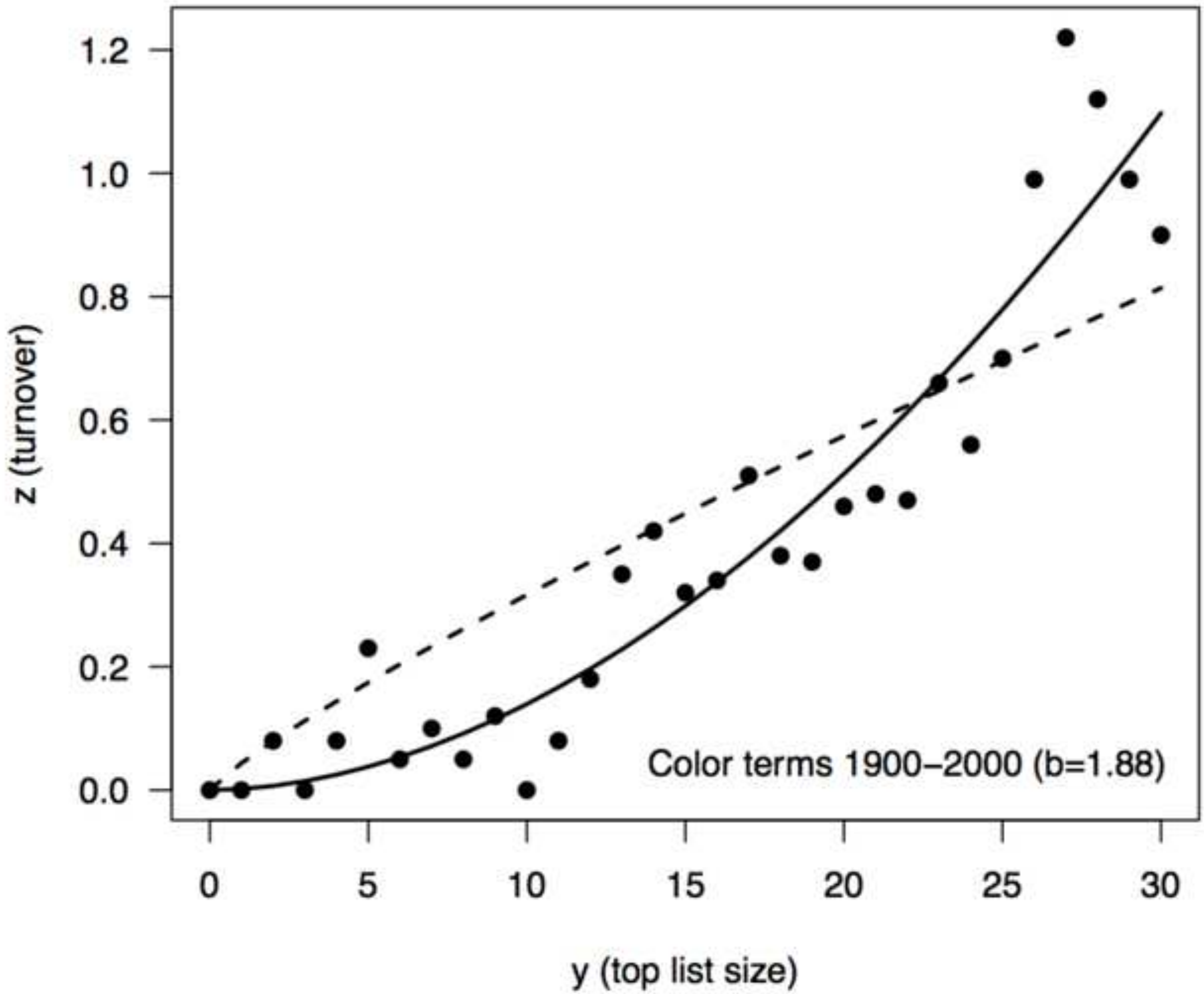

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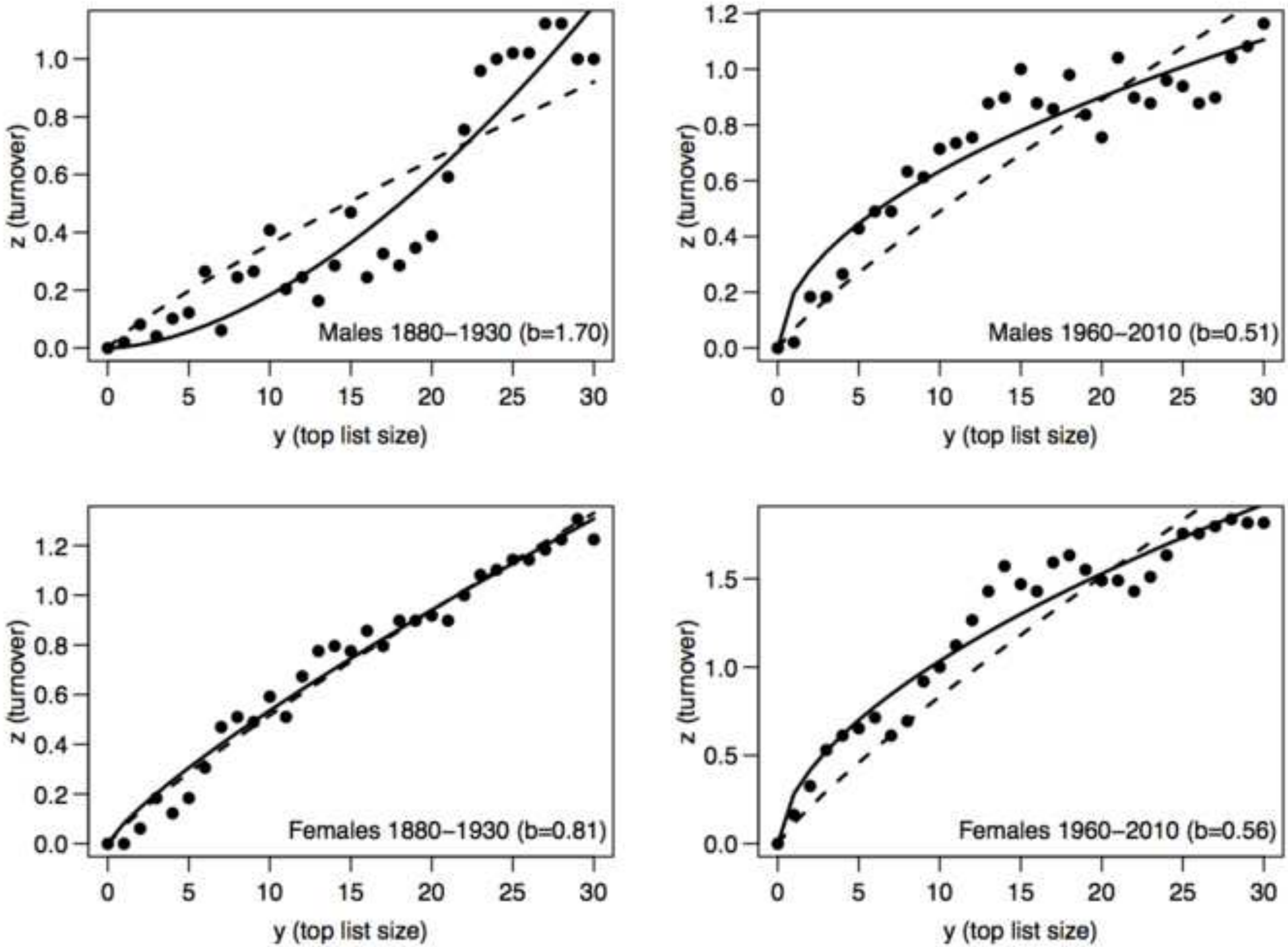

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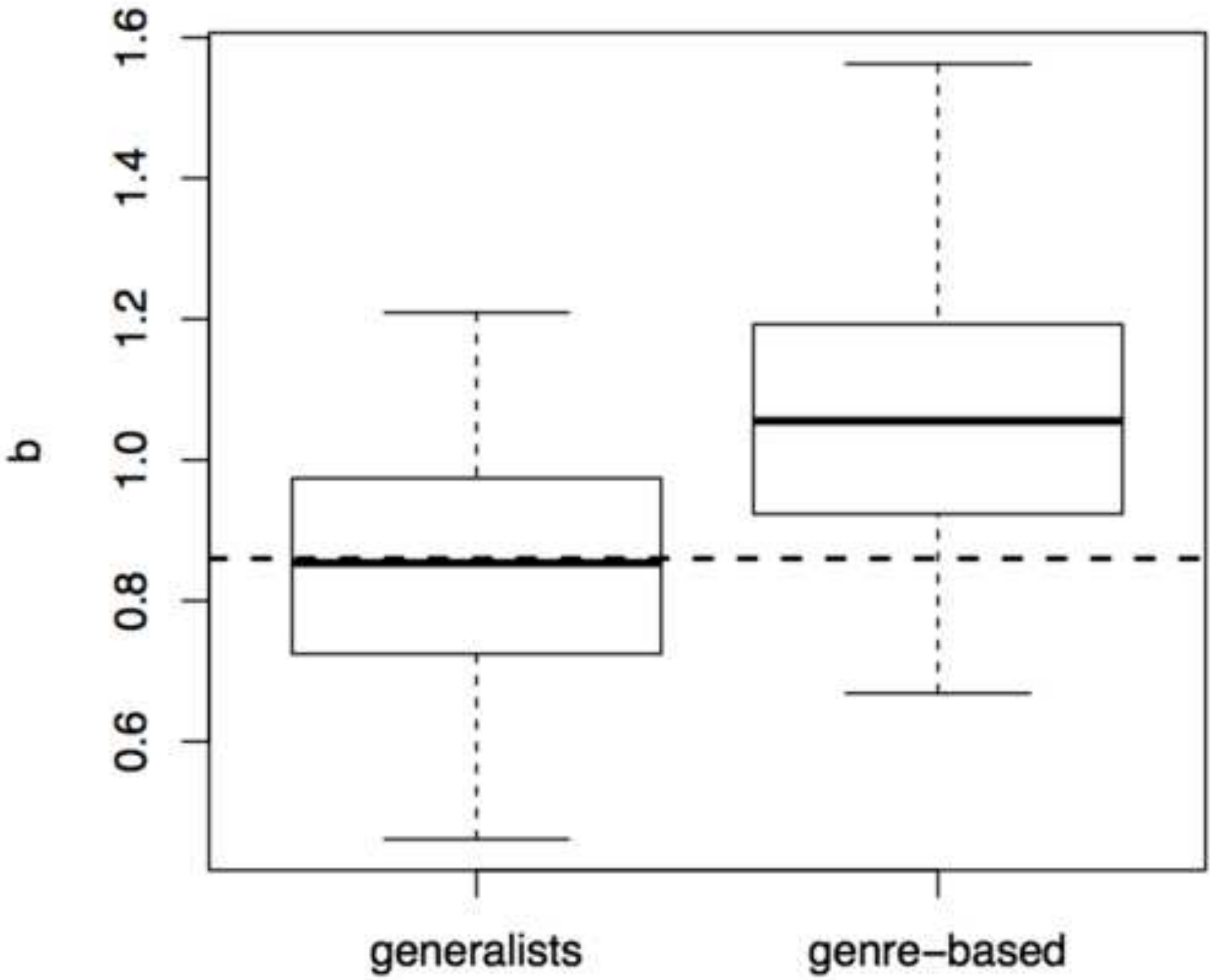

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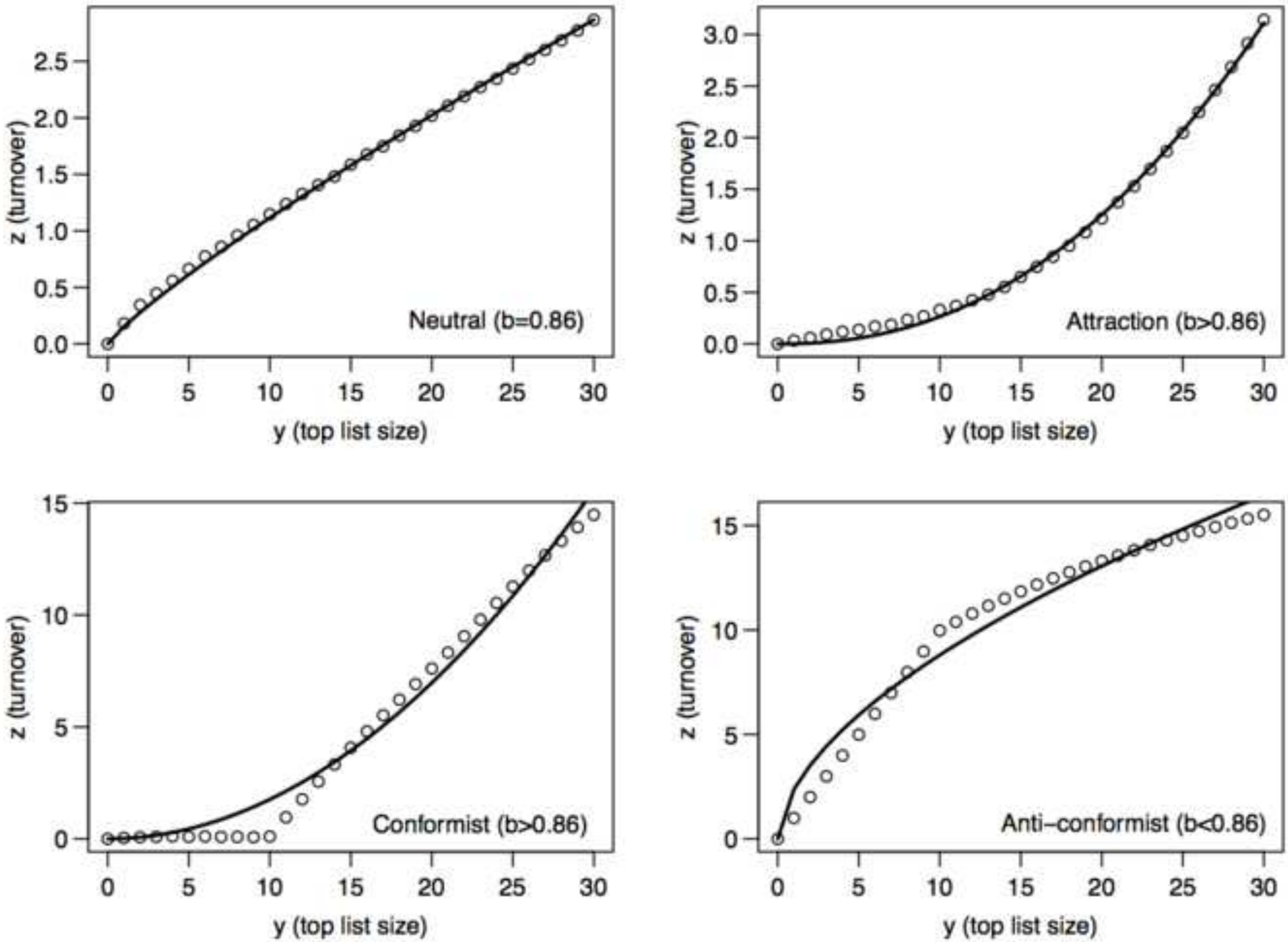

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