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Cultural evolution of emotional expression in 50 years of song lyrics

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Abstract

The cultural dynamics of music has recently become a popular avenue of research in the field of cultural evolution, reflecting a growing interest in art and popular culture more generally. Just as biologists seek to explain population-level trends in genetic evolution in terms of micro-evolutionary processes such as selection, drift and migration, cultural evolutionists have sought to explain population-level cultural phenomena in terms of underlying social, psychological and demographic factors. Primary amongst these factors are learning biases, describing how cultural items are socially transmitted from person to person. As big datasets become more openly available and workable, and statistical modelling techniques become more powerful, efficient and user-friendly, describing population-level dynamics in terms of simple, individual-level learning biases is becoming more feasible. Here we test for the presence of learning biases in two large datasets of popular song lyrics dating from 1965-2015 and 1965-2010, where we study the trends in emotional expression. We find an overall increase in emotionally negative lyrics and a decrease of positive ones. Our results provide some evidence of content bias, prestige bias and success bias in the proliferation of negative lyrics and decline of positive ones, and suggest that negative expression of emotions in music, and perhaps art generally, provides an avenue for people to not only process and express their own negative emotions, but also benefit from the knowledge that prestigious others experience similarly negative emotions as they do.

Keywords: cultural evolution; emotions; learning biases; song lyrics

Introduction

Are the lyrics of contemporary pop songs happier or sadder than the lyrics of the popular songs of previous generations? Do current songs talk about love more or less than they used to? In recent years, the availability of large data sets in electronic format has allowed such questions concerning long-term, population-level cultural dynamics to be addressed in an increasingly precise, quantitative, way [1]. This, in turn, permits researchers to test more general hypotheses about cultural trends and changes that previously could only be assessed informally by focusing on a small number of (potentially cherry-picked) cases.

A fruitful area of investigation concerns the analysis of emotions in human cultural expressions. Several tools have been developed to extract the emotional content of texts, also known as 'sentiment analysis'. Some of these provide a classification of how words score on 'positive' and 'negative' content [2], and others provide additional scores for specific emotions (e.g. how 'angry' or 'sad' is a text, [3]). In the majority of cases, sentiment analysis has been applied on a short-term time scale, e.g. social media interactions [4]. However, some researchers have explored a longer time scale, analysing the expression of emotions in several decades of song lyrics [5], newspaper articles [6], in Grimm's folktales [7], or in centuries of literary works [8].

The quantitative description of trends is fundamental, but a further necessary step is to understand what drives these trends. Cultural evolution theory [9–11] provides a series of concepts that allows such an endeavour. This research field draws a parallel between genetic evolution and cultural change, arguing that the latter can be seen as a Darwinian evolutionary process that shares fundamental similarities with, but also many differences to, genetic evolution. Inspired by biologists who seek to explain large-scale, long-term patterns and trends in genetic evolution in terms of individual-level processes such as selection, drift and migration, cultural evolutionists similarly seek to explain population-level patterns and trends in cultural systems in terms of individual-level social, psychological and demographic processes.

In particular, cultural evolutionists have focused on transmission or learning biases as key drivers of cultural evolutionary dynamics [12, 13]. Transmission biases are individual-level heuristics that individuals use to decide what, when, and from whom to copy. They are rule-of-thumb principles such as 'copy the majority', 'copy the successful', or 'copy the prestigious' that allow individuals to adaptively learn from others, on average [14]. Importantly, different transmission biases give rise to different population-level cultural dynamics. A cultural trait introduced in a population in which, for example, individuals copy mostly from their parents will spread slower than the same cultural trait introduced in a population in which individuals copy mostly from a few successful or prestigious individuals [9].

'Model-based' biases describe from whom people learn: for example, a success bias describes a tendency to learn from successful others, a prestige bias to learn from prestigious (high status, respected) others. Other 'content' biases describe what kind of information people learn best, due to its salience or memorability. For example, a bias to transmit emotionally salient content, or negative content, has been found in several lab experiments [15–18]. While there are many theoretical models that explore the conditions under which different transmission biases are adaptive and what their expected population-level consequences are [13] and experiments which have tested the predictions of these models in controlled laboratory set-ups [19–22], much less research has explored how cultural transmission biases may impact real-life cultural dynamics (although see [23–25]).

In this paper, we test the extent to which transmission biases can explain trends in the emotional content of two datasets of English language song lyrics. The first dataset ('billboard') contains the lyrics of the songs included in the annual Billboard Hot 100, a widely known US chart from 1965 to 2015 (N=4,913 songs). The second dataset ('mxm') contains the lyrics of the English language songs present in the musixmatch.com website, the world's largest lyrics platform where users can search and share lyrics, where we considered songs from 1965 to 2010 (N=159,293 songs).

Preliminary analyses found a substantial decrease in the use of *positive* emotions coupled with an increase in the use of *negative* emotion-related words in both datasets. Specific emotion-related words show considerable change in use during the time frame considered. For example, the use of the term 'love' more than halved in both datasets, whereas 'hate' increased substantially (see Figure 1 for the billboard dataset. The trends are qualitatively similar in the mxm dataset). These results are broadly consistent with previous analyses of song lyrics [5, 26] and literary fiction [27], pointing to the possible existence of a more general cultural or artistic trend for increasingly negatively valenced emotional expressions.

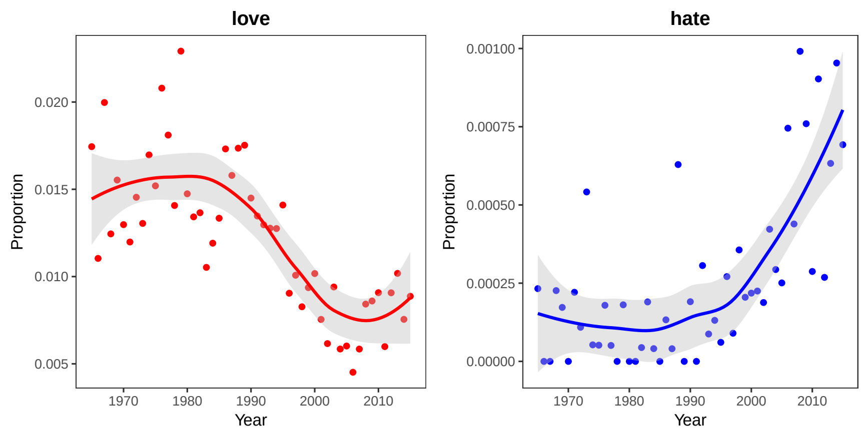

Figure 1 'Love' and 'hate' through years in the Hot 100 Billboard. Proportion of the term 'love' and 'hate' with respect to the year words total, for all the songs in the billboard dataset.

The main goal of this paper is to test hypotheses about possible drivers of these two trends. First, we checked whether linguistic effects could be causing the patterns. We considered a possible increase in slang words, an asymmetric semantic change (for which words denoting negative emotions had acquired positive or neutral connotation), and a general increase in lyrics complexity (notice the latter would predict that both negative- and positive-emotion words would decrease in frequency). After finding that the trend persisted after controlling for these linguistic effects (see Supplementary Information), we then considered whether cultural transmission biases might explain the pattern.

We consider, in a fully preregistered study, three hypotheses derived from cultural evolution theory as outlined above (see Methods section for how these verbal hypotheses were statistically implemented in our dataset):

- (H1) Success bias: the emotional trends result from artists copying the best selling songs from the preceding years.
- (H2) Prestige bias: the emotional trends result from artists copying the songs of 'prestigious' artists (independently from the success of the songs) from the preceding years.
- (H3) Content bias: there is a general human preference for lyrics that reflect negative emotions in songs, thus songs with more negative content rank higher in the charts.

Notice we applied H1 and H2 both to positive and negative content, while H3 is applied only to negative content, as we do not have predictions regarding content preferences towards positive emotions.

As our models are multi-level in nature, these hypotheses propose that the effects of success/prestige/content will be apparent whilst controlling for variation within artists, genre, and year of release.

Our results are mixed, in that we found a small effect of success bias on the likelihood of a word being positive in the billboard dataset, as well as a small effect of both prestige and content bias on the likelihood of a word being negative in the billboard dataset. However, these effects vastly reduced or became non-existent in the mxm dataset. We conclude that all three biases may play a small role in the likelihood of using positive or negative emotion words in song lyrics, but that these effects may be too small to be detected in big data, or may be swamped by other extraneous variables. We discuss possible explanations for the discrepancies between the billboard and mxm datasets, as well as our interpretation and implementation of success, prestige, and content biases in relation to the content of song lyrics.

Methods

Data preparation

'mxm' dataset

We downloaded (in August 2017) the full dataset (N=237,662 songs) from the musiXmatch dataset [28]. This dataset provides lyrics in bag-of-words form: each song is described as the word-counts for the top 5,000 words across the set. Rare terms are thus not recorded, but this does not affect our analysis, because all the emotion-words in the lists we used (see below) were among the top 5,000 We used the mxm track ID to retrieve from musixmatch.com the name of the artist(s), the year of first release, and the genre, for each track, and we integrate the information in the main dataset.

From the full dataset we eliminated songs for which it was not possible to retrieve the year or the artist, as well as songs that did not appear to be in English. To assess if a song was in English we simply checked whether the word 'the' was present at least once. We kept years for which at least 500 songs were included, therefore excluding songs published before 1965 or after 2010 (we kept the year 1970, even though the dataset contained 278 songs so as to retain a dataset with consecutive years). The new dataset comprised N=159,293 songs.

Artists' names were further processed using the cluster function in the *refinr* package in R [29] to cluster and merge similar names (e.g. 'madonna', 'Madonna', 'MADONNA'). To disambiguate collaborations we looked for standard separators in artist names ('featuring', 'feat.', 'feat, 'and', 'AND' ,'&', 'with', ','). We considered artists where no separators were found as single artists. We then ran the strings where separators were found (e.g. X and Y) through the list of single artists. If both X and Y were found in this list, then X and Y were considered as single artists occasionally collaborating (e.g. Eminem and Dr. Dre), and the song represented two (or more, if a collaboration of more artists) data points in our final analysis. If not, they were considered a stable collaboration(e.g. Simon and Garfunkel) or a band (e.g. The Mamas & the Papas) and a single data point in our models. The final dataset had thus N=161,587 data points.

'billboard' dataset

We downloaded (in May 2017) the data from the GitHub repository 'walkerkq/musiclyrics' [30]. This dataset provides the full lyrics for songs in the yearly Billboard Hot 100 chart, with few missing (N=4,913 songs). Since the lyrics in the mxm dataset are stemmed (a common practice in digital text analysis: words are reduced to their stems, roughly analogous to their morphological roots, e.g. 'happily', 'happy', and 'happiness' are all reduced to the stemmed form: 'happi'), we processed the billboard dataset in the same way, readapting the script used to process the mxm dataset, available in the author's GitHub repository [31] When, in what follows, we use 'word' or 'lyric' we are referring to the stemmed version. For consistency with the mxm dataset, we also discarded words that were not included in the list of the top 5,000 words described above.

Artists were further processed in the same way as the mxm dataset. Notice the 'genre' entry is not present in this dataset, as this information was not provided but, importantly, chart position is, which we coded as 'rank'. Rank is the song's chart position, from 1 to 100, in the yearly Billboard chart, where 1 indicates the best-selling and 100 indicates the least-selling song. The final dataset had N=5,878 data points.

Sentiment analysis tool

We used the 'positive emotions' and 'negative emotions' categories of the text analysis application Linguistic Inquiry and Word Count [3]. These categories are 'virtually unchanged' compared to the most recent (2015) version of LIWC (Pennebaker, pers. comm.). The words were stemmed as described above, and we analysed the lyrics with N=267 negative emotion stems and N=198 positive emotion stems. Thus each word of each song was classified as either positive, negative or neither.

Data analysis

We used Bayesian, aggregated binomial, multilevel models, to examine the effect of prestige, success and content bias on the likelihood of any given word being either positive or not, and negative or not. We used the *Rethinking* package in R [32] . We compared WAICs in a model comparison approach, but interpreted the parameter estimates of the full models in all cases. Model parameters were said to have an effect on the model outcome if their 89% credible interval did not cross zero. Priors were chosen to be weakly regularising, in order to control for both under and overfitting the model to the data. Due to the large number of data points that each model processed (each model of the mxm dataset processed roughly 29 million words), we had to implement a range of priors and adapt the models accordingly to ensure sufficient and appropriate mixing. Trace plots and effective sample sizes were used to check for appropriate model convergence throughout.

Full analysis scripts and data are available in the GitHub repository 'lottybrand22/song_lyrics' [33], and were preregistered through the Open Science Framework [34].

Levels of analysis

Each word of a song was coded, according to LIWC, as 'positive' (when present in the list of positive stems), 'negative' (when present in the list of negative stems) or neither. Thus, we implemented separate models for coding positive and negative lyrics (see Tables 1 and 2). Our models are aggregated binomial models, in that the words are aggregated within songs, but each word of a song is modelled as the binomial probability of being positive (or not). The negative models model the likelihood that each word in a song is negative (or not). This takes into account the fact that each song has a different number of words, and negates any need for averaging over words and songs. Each song is not an independent data point, as the data are clustered on artists, genre, and year of release. Thus, we implemented varying effects models, allowing adaptively regularising priors for the intercepts of artist, genre and year of release.

Our hypotheses

The success bias models assume that the probability that any given word in a song is positive (or negative) can be predicted by the average number of positive (or negative) words of the top ten songs in the preceding three years of the billboard list. Thus our variable 'success' for both mxm and billboard datasets, consisted of the average number of positive (or negative) words from the top ten songs of the billboard dataset (for the preceding three years of the song of interest).

The prestige bias models assume that the probability that any given word in a song is positive (or negative) can be predicted by the average number of positive (or negative) words of the prestigious artists in the preceding three years. We define prestigious artists as those that appeared more than 10 times in the Billboard Hot 100. This results in 86 'prestigious' artists (less than 4% of the total in the billboard dataset).

The content bias models assume that the probability that a word of a song will be negative is predicted by the rank of the song in the Billboard charts (see Tables 1 and 2 for specifications of all models in the two datasets).

Table 1 Details of model comparison results for the Billboard dataset models. The model with the lowest WAIC and highest proportion of the WAIC weight from each set is in bold.

Lyrics	Model	Parameters	WAIC	Weight	SE
Positive	Null	Artist|1 + Year|1	646946.3	0.12	1676.99
Positive	**Success bias**	**Success + Artist|1 + Year|1**	**646942.5**	**0.80**	**1677.00**
Positive	Prestige bias	Prestige + Artist|1 + Year|1	646948.8	0.03	1677.01
Positive	Full	Prestige + Success + Artist|1 + Year|1	646947.9	0.05	1676.93
Negative	Null	Artist|1 + Year|1	359482.2	0.0	1442.19
Negative	Success bias	Success + Artist|1 + Year|1	359488.9	0.0	1442.21
Negative	Prestige bias	Prestige + Artist|1 + Year|1	359493.1	0.0	1442.20
Negative	Content bias	Rank + Artist|1 + Year|1	359472.2	0.04	1442.17
Negative	**Full**	**Success + Prestige + Rank + Artist|1 + Year|1**	**359466.4**	**0.94**	**1442.21**

Table 2 Details of model comparison results for the mxm dataset models. The model with the lowest WAIC and highest proportion of the WAIC weight from each set is in bold.

Lyrics	Model	Parameters	WAIC	Weight	SE
Positive	**Null**	**Artist|1 + Genre|1 +Year|1**	**9481478**	**1**	**6651.86**
Positive	Success bias	Success + Artist|1 + Genre|1 + Year|1	9481503	0.0	6651.80
Positive	Prestige bias	Prestige + Artist|1 + Genre|1 + Year|1	9481502	0.0	6651.80
Positive	Full	Prestige + Success + Artist|1 + Genre|1 + Year|1	9481518	0.0	6651.89
Negative	**Null**	**Artist|1 + Genre|1 +Year|1**	**6602738**	**1**	**6057.61**
Negative	Success bias	Success + Artist|1 + Genre|1 + Year|1	6602763	0.0	6057.55
Negative	Prestige bias	Prestige + Artist|1 + Genre|1 + Year|1	6602754	0.0	6057.52
Negative	Full	Prestige + Success + Artist|1 + Genre|1 + Year|1	6602787	0.0	6057.53

Results

Model comparison

Our model comparison results suggested that, although some models hold the majority of the weight, their WAIC values are not very different from one another, and the standard errors of the differences show that there is a lot of uncertainty in the model comparison. Furthermore, we are aware that model comparison is less robust when modelling time-series data (McElreath, pers. comm.). Thus, we are reporting the results of the full models that include all of the effects of interest, while noting that the model comparison results should be interpreted with caution.

Models of positive lyrics using the billboard dataset

When modelling the likelihood that any word in the lyrics of a song is positive, the full model suggested that success had a positive effect (mean coefficient estimate: 0.04, 89% confidence interval: [0.00, 0.07], however prestige did not have a strong effect (0.02, CI:[-0.01,0.06]), see Figure 2

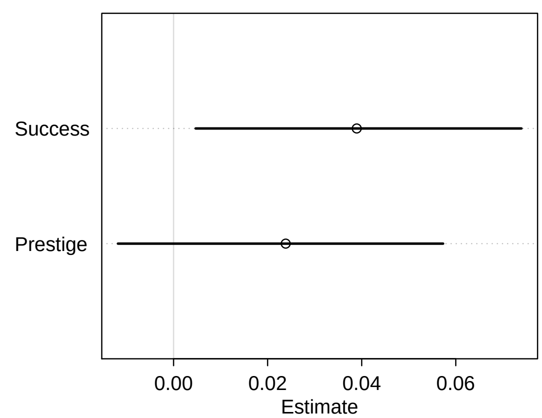

Figure 2 Parameter estimates for success and prestige from the full positive billboard model. Estimates include 89% confidence intervals. Estimates that cross zero are interpreted as not having a strong effect on the probability of a lyric being positive.

These effects are on the log-odds scale, and thus can be interpreted as the odds that a given word is positive increases by 4% as the number of positive words in the previous three years of top ten hits increases. The model comparison suggests support for H1, suggesting that our hypothesis that success-bias contributes to the proportion of positive lyrics was best supported, although there is a lot of uncertainty around the models' WAIC estimates.

Models of negative lyrics using the billboard dataset

When modelling the likelihood that any word in the lyrics of a song is negative, the full model suggested that prestige had a positive effect (mean coefficient estimate: 0.08, 89% CI: [0.01, 0.14], however success did not have a strong effect (0.01, CI:[-0.05,0.07]). Chart position had a negative effect, meaning songs that had a better chart position (e.g. closer to 1 rather than 100) increased the log odds of a lyric being negative (-0.02, CI:[-0.04,-0.01]), see Figure 3. The model prediction of the effect of prestige on the proportion of negative lyrics is shown in Figure 4. The model comparison suggested the best model was the full model, suggesting that prestige bias and content bias play a role in the proportion of negative lyrics, although there is a lot of uncertainty around the models' WAIC estimates.

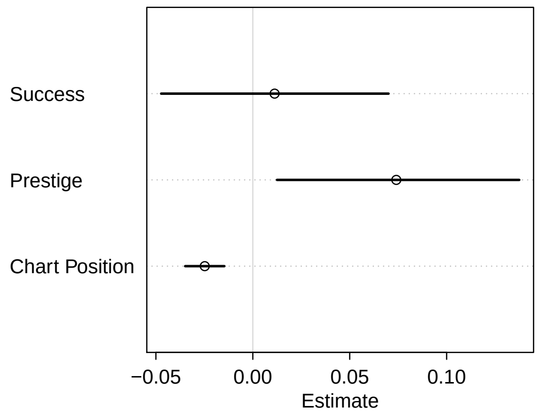

Figure 3 Parameter estimates for success, prestige and chart position from the full negative billboard model. Estimates include 89% confidence intervals. Estimates that cross zero are interpreted as not having a strong effect on the probability of a lyric being negative.

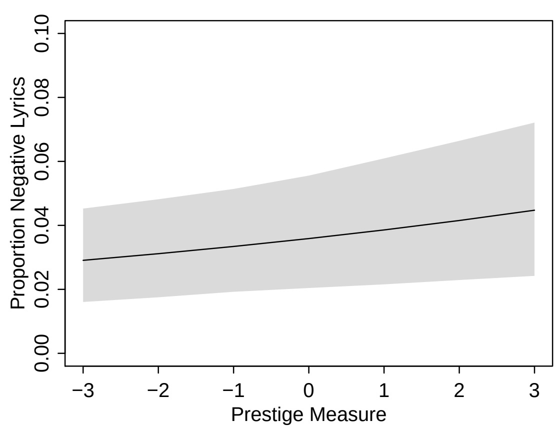

Figure 4 Effect of prestige measure on the proportion of negative lyrics in the billboard dataset. The prestige measure is scaled and centred on zero, so as the number of negative lyrics in prestigious artists' songs (from the previous 3 years) increase, so does the predicted proportion of negative lyrics in the current song.

Models of positive lyrics using the mxm dataset

When modelling the likelihood that any word in the lyrics of a song in the mxm dataset is positive, the full model suggested that prestige had a small positive effect (mean coefficient estimate: 0.01, 89% CI: [0.00, 0.02], however success did not have an effect (0.00, CI:[-0.01,0.01]), see Figure 5. The prestige effect is much smaller than those from the billboard models. Furthermore, the model comparison suggested the best model was the null model, suggesting that our parameters for success and prestige did not improve the model fit more than simply including the varying effects for artist, genre and year of release.

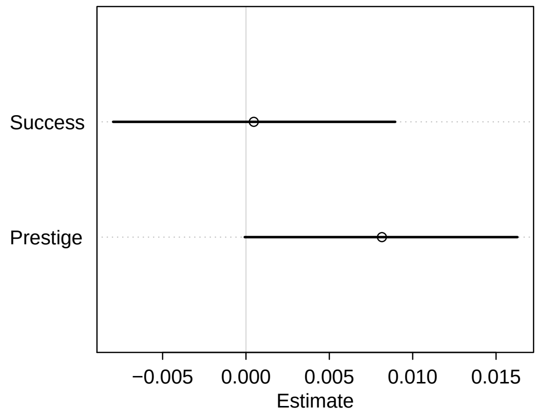

Figure 5 Parameter estimates for success and prestige from the full positive mxm model. Estimates include 89% confidence intervals. Estimates that cross zero are interpreted as not having a strong effect on the probability of a lyric being positive.

Models of negative lyrics using the mxm dataset

When modelling the likelihood that any word in the lyrics of a song be negative, the full model suggested that neither prestige nor success had an effect (prestige: 0.00, 89% CI: [-0.02, 0.01], success: 0.00, CI:[-0.01,0.01]), see Figure 6. Furthermore, the model comparison suggested the best model was the null model, suggesting that our parameters for success and prestige did not improve the model fit more than simply including the varying effects for year, artist, genre.

Discussion

We analysed the emotional content of song lyrics in around 165,000 songs spanning the years 1965-2015. We found that the frequency of negative words increased over time, whilst the frequency of positive words decreased over time, and asked whether these patterns could be attributed to cultural transmission biases, specifically success bias, prestige bias, and content bias. In the billboard dataset, containing top-100 songs from 1965 to 2015, we found small but measurable effects of success on positive lyrics, with the odds of any given word in a song being positive increasing by 4% when the previous three years of top ten hits contained more positive lyrics. For negative lyrics, we found small but measurable effects of artist prestige (the odds of any given word being negative increased with the number of negative words used by best-selling artists in the previous three years) and a negativity content bias (chart position was predicted by negative content). In the larger mxm dataset we found a weak effect of prestige for positive lyrics, and no effects for negative lyrics.

The effects of these biases are extremely small, which can partly be attributed to the fact that we analysed the data on the scale of each word, negating any need

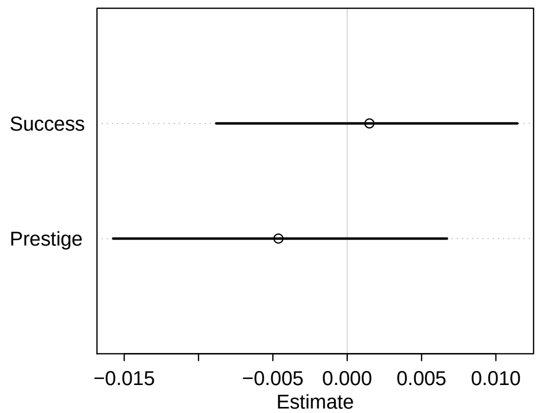

Figure 6 Parameter estimates for success and prestige from the full negative mxm model. Estimates include 89% confidence intervals. Estimates that cross zero are interpreted as not having a strong effect on the probability of a lyric being negative.

for averaging over lyrics and songs. Thus, the relative increase or decrease in the log odds are understandably small. These effects were uncovered despite a coarse and simplified implementation of success, prestige and content biases. It is therefore unsurprising that the effects vastly reduced or disappeared in the much larger mxm dataset given how many other factors must be at play in the generation of song lyrics, both directional biases such as those we explored here, and random chance [35]. For example, prestige can be realised in a myriad of ways, particularly in the music industry. The effect of various recording companies, the extent of media attention outside of the charts, the amount of money spent on music promotion, may all play a significant role, demonstrating that our implementation of 'prestige' only captures one small aspect of musical prestige.

The effect of prestige bias was stronger than the effect of success bias in two of the full models. This goes against theoretical predictions that, when success information is available, individuals should use success bias as it is a more direct and valid cue of social information compared to prestige information, which is usually an indirect measure, or secondary cue, of success [36]. This may reflect an over reliance on prestige bias in the domain of music, as artists often gain prestige which is inflated compared to their relative record sales or chart success. Moreover, prestige in the domain of music may be an example of 'runaway selection' in which an artist who is successful at one point in time, may then gain prestige due to their popularity and number of fans, leading to increased prestige over time which is decoupled from their musical expertise or success at a later point in time. It is worth noting that our implementation of prestige is a measure of an artists' overrepresentation in the charts compared to other artists in the charts. Thus, although our measure of prestige is separate from our measure of success in that an artist may be overrepresented in the charts overall, but not currently in the charts at a particular point in time, the measure may be more directly related to success than other implementations of prestige. Furthermore, in one of the full models, success bias was indeed a better predictor of positive lyrics than prestige bias.

The presence of a content bias in the likelihood of negative lyrics occurring in the billboard songs is noteworthy. This result suggests that songs with more negative lyrics are more successful in general, perhaps either reflecting a general negativity bias [15, 17], or an art-specific, or music-specific, negativity bias. Similar trends favouring negative emotions versus positive ones in other artistic domains support our finding. As mentioned, Dodds and Danforth [5] already documented an increase in frequency of positively-valenced words, and a decrease in negatively-valenced ones in pop song lyrics (a similar result is found in [26]). Morin and Acerbi [27] found a parallel effect in centuries of literary fiction, with a general decrease in the frequency of words denoting emotions, explained by a decrease in words denoting positive emotions, whereas the frequency of negative words remains constant. It is worth noting that we were unable to look for content bias (with our implementation) in the mxm data as there was no ranking system for the mxm data. One possible way of determining the popularity or use of a song could be to look at how many times, or how often, its lyrics are searched for, and whether this correlates with negative content.

In general, the idea that negative emotions would be privileged in art is consistent with the hypothesis that artistic expressions may have an adaptive function, in particular as simulation of social interactions [37]. According to this view, developed with literary fiction in mind but potentially generalisable to other expressive forms, art would provide hypothetical scenarios where we can test and train, with no risk, our cognitive and emotional reactions. In this perspective, simulating negative events is more useful than simulating positive ones [38, 39]. Art expressing negative emotions, in addition, may hold more value for audiences looking to seek comfort from the knowledge that others also experience negative emotions. Indeed studies have shown that people tend to underestimate the prevalence of others' negative emotions, and this underestimation exacerbates loneliness and decreases life satisfaction [40]. Furthermore, suppressing rather than reappraising negative emotions decreases self-esteem and increases sadness [41]. Taken together, the presence of prestige, success, and negativity biases may reflect a process by which people are generally comforted by others' negative emotional expression, and are particularly comforted when that person is prestigious or familiar. This hypothesis is worth investigating in future research.

Our varying effects models suggested that most of the variation lay between artists, however genre showed considerable variation too. We were unable to control for genre in the billboard data as genre information was not available with this dataset. This could provide a partial explanation for our differing results between the billboard and mxm datasets; indeed, Dodds and Danforth [5] attributed the decrease in emotional valence within pop song lyrics to the emergence of more negative genres such as heavy metal and punk. Future work investigating the variation of emotional expression between different genres of music would be valuable. A further limitation of this study is that we limited our analysis to comparing the content of each song with that of the songs from the previous three years' of songs. Mechanistically this suggests that songs that are currently in the charts influence song-writers who are writing within three years of chart success, assuming the time it takes to get from the song-writing process to chart success is three years or less.

Future work could test whether these effects are stronger or weaker at different time points, such as within 1 or 5 years of chart success. Furthermore, although we controlled for artist, many songs in the billboard charts are in fact written by specially designated song-writers, such as Max Martin. Investigating the effect of song-writer on the emotional expression within songs would be a fruitful avenue for future research.

Given the robustness of the trends and the relative weakness of the effects we found, as well as their inconsistency, this research points to the possibility that other factors are needed to explain the trends. It is possible to speculate, for example, that as standards of living increase, people get more cooperative and more trustful [42]. This, in turn, allows the expression of more sincere feelings in art, including more negative emotions. Commercial interest may also have played a role. Media and producers could have artificially inflated the presence and the success of songs with positive emotions in the early years of commercial diffusion of popular music, so that the trend we observe could be simply interpreted as a regression to the mean after an exaggerated positive peak in the 50s of last century, as Morin and Acerbi [27] mention for literary fiction and the possibility of an 'emotional peak' in the Romantic era.

Overall this research contributes to the growing body of work attempting to quantitatively study trends in the domain of music. Our starting result of an increase in negative emotions and decrease in positive ones in song lyrics is paired by similar findings regarding acoustic qualities. Using the same Billboard Hot 100 songs that we analysed, Schellenberg and von Scheve [43] found an increase in minor mode and a decrease in the average tempo, which indicate that the songs become more sad-sounding through time. This seems to be part of a longer trend in western classical music, where the use of the minor mode had increased in a 150-year period from 1750 to 1900 [44]. The relationship between minor tone and negative valence of lyrics has been also studied, and confirmed, quantitatively [45]. Analogously, studying more than 500,000 songs released in UK between 1985 and 2015, Interiano et al. [46] found a similar decrease in 'happiness' and 'brightness', coupled with a slight increase in 'sadness' (these high-level features result from algorithms analysing low-level acoustic features, such as the tempo, the tonality, etc.). They also found the puzzling result that, despite a general trend towards sadder songs, the successful hits are, on average, happier than the rest of the songs. In the same way, whereas we found that the higher the position in the billboard chart the more negative a song is, billboard songs are as a whole more positive than the songs in the mxm dataset, which contains more (and less successful) songs.

More specifically, in our research we apply cultural evolutionary theory to understand these trends [47–50]. It holds value in contributing to the growing body of work demonstrating the precision with which one can model large datasets, revealing evidence of underlying behaviour at the individual level. Not only does research of this nature help to integrate cultural evolution theory with the arts and humanities, but also contributes to our understanding of how culture influences the expression of emotions [51] Exploring the cultural evolution of music is becoming a valuable and rich area of research for revealing the cultural transmission mechanisms that can underpin some of the most pervasive of human cultural practices such as music production.

Availability of data and materials
The datasets generated and analysed during the current study are available in the Github repository: https://github.com/lottybrand22/song_lyrics and were generated from data available in the Github repository: https://github.com/walkerkq/musiclyrics and in the musiXmatch dataset, available at: https://labrosa.ee.columbia.edu/millionsong/musixmatch

Competing interests
The authors declare that they have no competing interests.

Author's contributions
All authors developed the research questions and designed the analyses. AA collected the original data; COB analyzed the data; AA and COB prepared the figures and the tables. All authors wrote the manuscript. All authors read and approved the final manuscript.

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