How algorithmic popularity bias hinders or promotes quality

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Abstract

Algorithms that favor popular items are used to help us select among many choices, from engaging articles on a social media news feed to songs and books that others have purchased, and from top-raked search engine results to highly-cited scientific papers. The goal of these algorithms is to identify high-quality items such as reliable news, beautiful movies, prestigious information sources, and important discoveries — in short, high-quality content should rank at the top. Prior work has shown that choosing what is popular may amplify random fluctuations and ultimately lead to sub-optimal rankings. Nonetheless, it is often assumed that recommending what is popular will help high-quality content “bubble up” in practice. Here we identify the conditions in which popularity may be a viable proxy for quality content by studying a simple model of cultural market endowed with an intrinsic notion of quality. A parameter representing the cognitive cost of exploration controls the critical trade-off between quality and popularity. We find a regime of intermediate exploration cost where an optimal balance exists, such that choosing what is popular actually promotes high-quality items to the top. Outside of these limits, however, popularity bias is more likely to hinder quality. These findings clarify the effects of algorithmic popularity bias on quality outcomes, and may inform the design of more principled mechanisms for techno-social cultural markets.

Introduction

Cultural markets, such as social media, the entertainment industry, and the world of fashion are known for their continuous rate of innovation and inherent

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unpredictability. Success of individual actors (e.g., artists) or products (e.g., songs, movies, memes) is in fact hard to predict in these systems [34, 35, 24], mainly due to the presence of strong social reinforcement, information cascades, and the fact that quality is ultimately predicated on intangible or highly subjective notions, such as a beauty, novelty, or virality.

In the absence of objective and readily measurable notions of quality, easily accessible metrics of success — such as the number of downloads of a song, or the number of social media followers of an individual — are often taken as input for future recommendations to potential consumers. Popularity and engagement metrics are intuitive and scalable proxies for quality in predictive analytics algorithms. As a result, we are exposed daily to rankings that are based at least partially on popularity, from bestseller lists to the results returned by search engines in response to our queries [5].

The usefulness of such rankings is predicated on the wisdom of the crowd [33]: high-quality choices will gain early popularity, and in turn become more likely to be selected because they are more visible. Furthermore, knowledge of what is popular can be construed as a form of social influence; an individual’s behavior may be guided by choices of peers or neighbors [23, 19, 20, 18, 29, 2, 6]. These mechanisms imply that, in a system where users have access to popularity or engagement cues (like ratings, number of views, likes, and so on), high-quality content will “bubble up” and allow for a more cost-efficient exploration of the space of choices. This is such a widely shared expectation that social media and e-commerce platforms often highlight popular and trending items.

Popularity based metrics, however, can bias future success in ways that do not reflect or that hinder quality. This can happen in different ways. First, lack of independence and social influence among members of the crowd — as that implicitly induced by the availability of rankings — severely undermines the reliability of the popularity signals [21]. Second, engagement and popularity metrics are subject to manipulation, for example by fake reviews, social bots, and astroturf [27, 9].

Popularity bias can have more subtle effects. The use of popularity in ranking algorithms by search engines was alleged to impede novel content from rising to the top, but such an entrenchment effect was shown to be mitigated by diverse user queries [10]. In social media, some memes inevitably achieve viral popularity in the presence of competition among networked agents with limited attention, irrespective of quality [34], and the popularity of memes follows a power-law distribution with very heavy tails [13]. Mechanisms such as unfriending and triadic closure facilitate the formation of homogeneous “echo chambers” [32] or “filter bubbles” [24] that may further distort engagement metrics by selective exposure.

Even in the absence of engineered manipulation or social distortion, quality is not necessarily correlated with popularity. Consumers face a trade-off between performing cognitively expensive but accurate assessments based on quality and cognitively cheaper but less accurate choices based on popularity. Adler has shown that the cost of learning about quality will lead to “stars” with disproportionate popularity irrespective of differences in quality [11]. Such trade-
offs are common in social learning environments [28]. Salganik et al. created a music-sharing platform to determine under which conditions one can predict popular musical tracks [29]. The experiments showed that in the absence of popularity cues, a reliable proxy for quality could be determined by aggregate consumption patterns. However, popularity bias — for example when users were given cues about previous downloads of each track — prevented the quality ranking from being recovered. By influencing choices, popularity bias can reinforce initial fluctuations and crystallize a ranking that is not necessarily related to the inherent quality of the choices [16]. This can happen even in the absence of explicit social signals, if the observed ranking is biased by popularity [15]. Similar results have been found in other studies [30, 31, 18, 12] and have spurred a renewed interest in the topic of predictability in cultural markets. Van Hentenryck et al. studied a model of trial-offer markets to analyze the effect of social influence in market predictability [14]. In this model, users chose from a list of items ranked by quality rather than popularity; this modification makes the market predictable and aligns popularity and quality. Becker et al. addressed the question of which network structure is most conducive to the wisdom of the crowd when people are influenced by others [3].

The conditions in which popularity bias promotes or hinders quality content have not been systematically explored. Here we do so by studying an idealized cultural market model in which agents select among competing items, each with a given quality value. A parameter regulates the degree to which items are selected on the basis of their popularity rather than quality. We find that this popularity bias yields a rich behavior when combined with the cognitive cost of exploring less popular items. There exists an optimal trade-off in which some popularity bias results in maximal average quality, but this trade-off depends on the exploration cost.

Results

Our model considers a fixed number $N$ of items. These represent transmissible units of information, sometimes referred to as memes [7], such as music tracks, videos, books, fashion products, or links to news articles. Items are selected sequentially at discrete times. Each item $i$ has an intrinsic quality value $q_i$ drawn uniformly at random from $[0, 1]$. Quality is operationally defined as the probability that an item is selected by a user when not exposed to the popularity of the item. The popularity of item $i$ at time $t$, $p_i(t)$, is simply the number of times $i$ has been selected until $t$. At the beginning each item is equally popular: $p_i(0) = 1, i = 1 \ldots N$.

At each time step, with probability $\beta$, an item is selected based on its popularity. All items are first ranked by their popularity, and then an item is drawn with probability proportional to its rank raised to some power:

$$P_i(t) = \frac{r_i(t)^{-\alpha}}{\sum_{i=1}^{N} r_i(t)^{-\alpha}}$$

(1)
where the rank \( r_i(t) \) is the number of items that, at time \( t \), have been selected at least as many times as \( i \). The exponent \( \alpha \) regulates the decay of selection probability for lower-ranked items. This schema is inspired by the ranking model, which allows for the emergence of scale-free popularity distributions with arbitrary power-law exponents \([11]\); it is consistent with empirical data about how people click search engine results \([10]\) and scroll through social media feeds \([26]\). This model could accurately capture aggregate behavior even if individuals followed different selection schemes \([8]\).

Alternatively, with probability \( 1 - \beta \), an item is drawn with probability proportional to its quality:

\[
P_i = \frac{q_i}{\sum_{i=1}^{N} q_i}.
\]

After an item \( i \) has been selected, we update its popularity \( (p_i(t+1) = p_i(t) + 1) \) and the ranking. Two items will have the same rank \( r \) if they have been selected the same number of times. If \( k \) item are all at the same rank \( r \), then the next rank will be \( r + k \).

The model has two parameters: \( \beta \) regulates the importance of popularity over quality and thus represents the popularity bias of the algorithm. When \( \beta = 0 \), choices are entirely driven by quality (no popularity bias). When \( \beta = 1 \), only popularity choices are allowed, yielding a type of Polya urn model \([22]\). The parameter \( \alpha \) can be thought of as an exploration cost. A large \( \alpha \) implies that users are likely to consider only one or a few most popular items, whereas a small \( \alpha \) allows users to explore less popular choices. In the limit \( \alpha \to 0 \), the selection no longer depends on popularity, yielding the uniform probability across the discrete set of \( N \) items.

We vary \( \beta \) systematically in \([0, 1]\) and consider different values of \( \alpha \) between 0 and 3. We simulate 1,000 realizations for each parameter configuration. In each realization we perform \( T = 10^6 \) selections using Eqs. 1 and 2 and store the final popularity values.

We characterize two properties of the final distribution of popularity \( \{p_i\}_{i=1}^{N} \) with respect to the intrinsic quality distribution \( \{q_i\}_{i=1}^{N} \). For brevity, we pose \( p_i = p_i(T) \) here. The first quantity we measure is the average quality \( \bar{q} = \sum_{i=1}^{N} p_i q_i / \sum_{i=1}^{N} p_i \) and the second property \( \tau \) is the faithfulness of the algorithm, i.e., the degree to which quality is reflected in popularity. We quantify faithfulness using Kendall’s rank correlation between popularity and quality \([17]\).

We can derive the values of both properties in the extreme cases of maximum or no popularity bias. When \( \beta = 0 \), selections are made exclusively on the basis of quality and therefore one expects \( p_i \to q_i \) as \( T \to \infty \). The rankings by quality and popularity are therefore perfectly aligned, and \( \tau = 1 \). In the limit of large \( N \) we can make a continuous approximation \( \bar{q} \to \int_{0}^{1} q^2 dq / \int_{0}^{1} q dq = 2/3 \). When \( \beta = 1 \), quality never enters the picture and any permutation of the items is an equally likely popularity ranking, which translates into \( \tau = 0 \). Also \( p_i \to 1/N \) and in the continuous approximation \( \bar{q} \to \int_{0}^{1} q dq = 1/2 \). What happens for intermediate values of popularity bias is harder to predict. The question we ask is whether it is possible to leverage some popularity bias to obtain a higher
average quality, even at the cost of decreasing the algorithm’s faithfulness.

The dependence of the average quality \( \bar{q} \) on the popularity bias \( \beta \) and exploration cost \( \alpha \) is shown in Fig. 1(a,b). We observe that if \( \alpha \) is small, popularity bias only hinders quality; the best average quality is obtained for \( \beta = 0 \). However, if \( \alpha \) is sufficiently large, an optimal value of \( \bar{q} \) is attained for \( \beta > 0 \). The location of the maximum \( \bar{q} \) as a function of \( \beta \) depends non-trivially on the exploration cost \( \alpha \). When popularity-based choices are strongly focused on the top-ranked items (\( \alpha > 1 \)), \( \beta \) is a decreasing function of \( \alpha \). Overall, the highest value of \( \bar{q} \) is observed for \( \alpha = 1 \) and \( \beta \approx 0.4 \).

In Fig. 1(c,d) we show the behavior of faithfulness \( \tau \) as a function of \( \alpha \) and \( \beta \). We observe that popularity bias always hinders the algorithm’s faithfulness, however the effect is small for small \( \beta \). This suggests that in the regime where popularity bias improves quality on average, there is a small price to be paid in terms of over-represented low-quality items and under-represented higher-quality items. If these mistakes occur in the low-quality range, they will not affect the average quality significantly. In general, the algorithm can retain
faithfulness in the presence of moderate popularity bias, even when the average quality is poor. When $\alpha$ is large, $\tau$ remains high over a wide range of popularity bias values. In this regime, the preference for popular items is so strong that the vast majority of items (those that do not make the top of the ranking early on) are chosen only by quality-based choice, and therefore their relative ranking perfectly reflects quality. The average quality is however hindered by the top-ranked items, which are selected via popularity irrespective of low quality.

In summary, our results show that some popularity bias, together with a mild exploration cost, can produce excellent average quality with minimal loss in faithfulness. Optimizing the average quality of consumed items requires a careful balancing of quality- and popularity-based choices as well as a fine tuning of the focus on the most popular items. For a given value of $\beta$, if $\alpha$ is too low, the popularity bias hinders quality because it fails to enhance the signal provided by the quality-based choices. To understand why quality is also hindered by the popularity bias when $\alpha$ is too high, consider the evolution of the average quality in simulations of the model for different values of $\alpha$ and $\beta$, shown in Fig. 2. By focusing only on the top ranked items ($\alpha = 2$), the system converges prematurely to a sub-optimal ranking, producing lower quality on average. In other words, with insufficient exploration the popularity bias risks enhancing initial noise rather than the quality-based signal. With more exploration ($\alpha = 1$), $\bar{q}$ continues to grow. The premature convergence to sub-optimal ranking caused by excessive popularity bias is also reflected in the increased variance of the average quality across runs of the model for larger values of both $\alpha$ and $\beta$. This is consistent with the increase in variance of outcomes observed in other studies [29, 16].
Discussion

Cultural markets like social media and the music and fashion industry account for multi-billion businesses with worldwide social and economic impact [25]. Success in these markets may strongly depend on structural or subjective features, like competition for limited attention [34, 26]. The inherent quality of cultural products is often difficult to establish, therefore relying on measurable quantitative features like the popularity of an item is hugely advantageous in terms of cognitive processing and scalability.

Yet, previous literature has shown that recommending already popular choices can be detrimental to the predictability and overall quality of a cultural market [29]. This left open the question of whether there exist situations in which a bit of popularity bias can help high-quality items bubble up in a cultural market.

In this paper we answered this question using an extremely simplified abstraction of cultural market, in which items are endowed with inherent quality. The model could be extended in many directions, for example assuming a population of networked agents with heterogeneous parameters. However, our approach leads to very general findings about the effects of popularity bias. While we confirmed that such a bias distorts assessments of quality, the scenario emerging from our analysis is less dire than suggested by prior literature. First, it is possible to maintain a good correspondence between popularity and quality rankings of consumed items even when our reliance on popularity for our choices is relatively high. Second, it is possible to carefully tune the popularity mechanisms that drive our choices to effectively leverage the wisdom of the crowd and boost the average quality of consumed items.

From a normative perspective, our results provide a recipe for improving the quality of content in techno-social cultural markets driven by engagement metrics, such as social media platforms. It is possible in these systems to estimate the exponent $\alpha$ empirically, by measuring the probability that a user engages with an item as a function of the item’s position in the feed. Given a statistical characterization (e.g., average or distribution) of the exploration cost, the bias $\beta$ of the ranking algorithm can be tuned to maximize expected average quality.

These findings are important because in our information-flooded world we increasingly rely on algorithms to help us make consumption choices. Platforms such as search engines, shopping sites, and mobile news feeds save us time but also bias our choices. Their algorithms are affected by and in turn affect the popularity of products, and ultimately drive what we collectively consume in ways that we do not entirely comprehend. It has been argued, for example, that the engagement bias of social media ranking algorithms is partly responsible for the spread of low-quality content over high-quality material [4]. Evaluating such a claim is challenging, but the present results may lead to a better understanding of algorithmic bias.
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