Parametric Empirical Bayes for Predicting Quality in Rating Systems

Thomas Ma, Ramesh Johari, Michael S. Bernstein
{tma98,rjohari,mbernst}@stanford.edu
Stanford University
Stanford, California, USA

Nikhil Garg
ngarg@cornell.edu
Cornell Tech
New York, New York, USA

ABSTRACT
User-solicited ratings systems in online marketplaces suffer from a cold-start problem: new products have very few ratings, which may capture overly pessimistic or optimistic views of the proper rating of that product. This could lead to platforms promoting new products that are actually low quality, or cause high-quality products to get discouraged and exit the market early. In this paper, we address this cold-start problem through an approach that softens early reviews, interpolating them against a background distribution of product ratings on the platform. We instantiate this approach using a parametric empirical Bayes model, which weighs reviews of a new product against expectations of what that product’s quality ought to be based on previous products that existed in the same market, especially when the number of reviews for that new product are low. We apply our method to real-world data drawn from Amazon as well as synthetically generated data. In aggregate, parametric empirical Bayes performs better on predicting future ratings, especially when working with few reviews. However, in these same low-data settings, our method performs worse on individual products that are outliers within the population.

CCS CONCEPTS
• Mathematics of computing → Bayesian computation; Bayesian computation; • Human-centered computing → Reputation systems; Human computer interaction (HCI); • Information systems → Electronic commerce; Reputation systems; • General and reference → Empirical studies.

KEYWORDS
reputation systems, Bayesian methods, online marketplaces

ACM Reference Format:
Thomas Ma, Ramesh Johari, Michael S. Bernstein and Nikhil Garg. 2022. Parametric Empirical Bayes for Predicting Quality in Rating Systems. In Proceedings of Workshop on Decision Intelligence and Analytics for Online Marketplaces (KDD ’22). ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

KDD ’22, August 14–18, 2022, Washington, D.C.
© 2022 Association for Computing Machinery.
ACM ISBN 978-x-xxxx-xxxx-x/YY/MM . . $15.00
https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION
Online marketplaces that rely on user-generated ratings to judge the quality of listings on their platform, such as Amazon or Uber, suffer from a cold-start problem, where a new listing is unable to be rated accurately because it has little to no review data. This impacts the ability for new listings with a single bad rating to gain notoriety, and also allows for bad listings that happen to receive a few good reviews to be unfairly promoted. Cold-start’s consequences are well-documented in the context of recommender systems, where it is referred to as the new user problem [13], and it is particularly problematic for online labour markets, where workers with little experience are unlikely to be hired [16].

Most online marketplaces calculate the estimated quality score of a product on the market using previous ratings that product has received, most commonly in the form of a sample mean. This leads to a problem in the context of cold-start; the first few ratings for a product could simply be the result of luck or malicious behaviour. For example, a high-quality product may have just gotten unlucky with a few bad ratings, or a poor-quality product may have found a way to “buy” a batch of fraudulent reviews (perhaps by leaving high-quality ratings through sock-puppet accounts). As such, the naïvely estimated quality of the product from early ratings alone might not correspond to the actual ratings a product gets in the future. A better solution would be to be more lenient to new products with few ratings, or, better yet, consider information about how other similar products performed when they had only a few ratings.

We suggest a parametric empirical Bayes (EB) algorithm to estimate the quality of a product, which takes into account more than just the past reviews of a product to generate a quality estimate. EB is a Bayesian estimation process; it assumes that there exists some prior distribution of quality from which products are drawn, and uses the individual ratings of the product to compute a posterior. Rather than use an uninformative prior or assume some outside knowledge about the parameters of the prior, EB fits this prior through empirical observations about the distribution of ratings in the overall population. This simple-to-use method exploits the fact that most online marketplaces have large amounts of parallel data at the product level: there are many items on the market, each of which have their own ratings data. When a new product enters the market, we should be able to leverage our knowledge about similar products that already exist to temper our expectations of the quality of the new good. Using the average quality of each product in a population, we can fit a prior over what the quality of a new good in an existing population will be. We then treat any user reviews for that new good as updates to the prior distribution, using this information to present a quality estimate.
We test this approach on a dataset of Amazon reviews, comparing the quality of estimation to naively computing the sample mean (what we call the *frequentist approach*), with a particular interest in how either method works in low data regimes. To control for potential selection issues in the data generation process, we also replicate this analysis on synthetic data. We find that for all datasets, the empirical Bayes approach has lower overall mean-squared error, with dramatic improvements on products with few ratings: On the Amazon dataset, we achieve an average 72% reduction in mean-squared error when the EB algorithm sees a product with 10 or fewer reviews. However, EB also gives less accurate predictions on “outlier” products that have unusually high or low quality scores relative to the population, until enough ratings are received for the outlier to overcome EB’s initial skepticism. We finish with a discussion of why we believe an implementation of our model in a real-world market would require modelling the ratings generation process as endogenous to the model, rather than simply being given as training data.

2 RELATED WORK

Empirical Bayes methods have been well-studied and widely used in statistics literature since their introduction by Robbins [18], most notably for the method’s applications in statistical decision theory [17]. Empirical Bayes also has a long history of being used for statistical inference [2, 6, 14]; to our knowledge, our work is the first to use EB for statistical inference rating systems for online marketplaces. Ignatiadis and Wager [11] infer the quality of movies with empirical Bayes estimators when one has access to feature-level data for each movie in addition to ratings, but mainly emphasize the general minimax optimality bounds for their approach.

On the ratings system side of literature, user-generated reviews as a feedback system have become increasingly widespread in online platforms over the past two decades [5]. Empirical experiments have shown the importance of early ratings on a product’s success on online marketplaces [4], as well as the possible impacts that social influence can have on an item’s success [3, 19]. To investigate these effects, many empirical studies have implemented novel rating systems and analyzed their impacts: Gaikwad et al. [7] design an online labour marketplace where the raters’ judgements have consequences for future transactions, while Garg and Johari [9] assess how changing the language of the surveys presented to raters can drastically alter ratings scores. From a more theoretical, model-building perspective, Garg and Johari [8] designed an optimal ratings system to recover the true quality of products in a *binary* rating system where the rating can either be 0 (dislike) or 1 (like). Most related to our work, Kokkodis and Ipeirotis [12] use Bayesian methods and linear dynamical systems to predict the quality scores of individuals in online labour markets when those individuals participate in multiple different categories of work.

3 MODEL AND METHOD

In this section, we develop a model to formalize our ratings problem. The key assumption of this model is that every product in an online market has a true quality score that is drawn from an underlying *population distribution* of items, and that, with enough ratings data for an individual product, the estimated quality of that product resembles the true quality. Our goal will be to estimate the true quality of a product, even if there are not many ratings for it. We take a Bayesian approach: We will treat the population distribution as our prior, and the ratings-generation process for a single product as our data-generating process.

We assume we are given a dataset of products $R$, with each product having some number of 1-, 2-, 3-, 4-, and 5-star ratings. While EB is a statistical method that works for many distributions, for simplicity, we model each product $r \in R$ as generating ratings according to a multinomial distribution with event probability parameters $p_{1r}, \ldots, p_{5r}$. Each product $r$ has $N_r$ reviews, with $r_j$ referring to the number of $i$-star reviews garnered by a product.

For each product $r$, we model $(p_{1r}, \ldots, p_{5r})$ as being drawn from a Dirichlet distribution with parameters $\alpha = (\alpha_1, \ldots, \alpha_5)$, which represents a population that the products are being drawn from. Unlike a traditional Bayesian approach, in which the parameters of the prior are either set to be uninformative or given as hyperparameters, in parametric empirical Bayes, we fix $\alpha$ using population-level data. For each product $r$, we estimate the event probability parameter for an $i$-star review to be $\hat{p}_{ir} = r_i / N_r$. This reflects our assumption that, provided each product in the training dataset has enough reviews, the estimated event probability parameter resembles the true event probability parameter.

We use these estimates to calculate a maximum-likelihood estimate of $\alpha$. To compute MLEs $\hat{\alpha}_1, \ldots, \hat{\alpha}_5$ from the set of probability parameter estimates $(\hat{p}_{1r}, \ldots, \hat{p}_{5r})_{r \in R}$, we use an iterative method for calculating the maximum likelihood estimators of the Dirichlet distribution parameter [10]: If $\tilde{\alpha}_{ij}$ is the estimate for $\alpha_i$ at iteration $t$, the update rule is

$$\tilde{\alpha}_{t+1, ij} = \psi^{-1} \left( \psi \left( \sum_{j=1}^{5} \tilde{\alpha}_{t, j} \right) + \frac{1}{N} \sum_{r \in R} \log(p_{ir}) \right),$$

where $\psi$ is the digamma function. We iterate until convergence is achieved, getting the prior parameter estimate $\hat{\alpha} = (\hat{\alpha}_1, \ldots, \hat{\alpha}_5)$. To estimate the quality of a new product $d$ with observed number of $i$-star reviews $d_i$ for $i \in \{1, \ldots, 5\}$, we exploit conjugacy and find

$$\text{prob}(p_{1d}, \ldots, p_{5d} | d_1, d_2, \ldots, d_5) \sim \text{Dirichlet}(\hat{\alpha}_1 + d_1, \ldots, \hat{\alpha}_5 + d_5)$$

We compute the posterior mean estimates $(\tilde{p}_{1d}, \ldots, \tilde{p}_{5d})$ from this distribution as our empirical Bayes estimates of the event probability parameter of getting an $i$-star review for product $d$.

Throughout the next section, we contrast quality estimates derived from these posterior means with the *frequentist approach* for estimating product quality, which we define here to simply be the sample mean of a product’s existing ratings: If we have a new product $d$ with observed number of $i$-star reviews $d_i$ for $i \in \{1, \ldots, 5\}$, the frequentist approach estimate of $\mu_d$ is simply $d_i / \sum_i d_i$. This is equivalent to the maximum likelihood estimator in a frequentist setting, and is what many large online platforms, like Uber, use for calculating estimated quality scores [1].

4 EXPERIMENTS

The primary goal of our experiments is to investigate how our empirical Bayes estimation method compares to traditional frequentist methods.
estimation. We are particularly interested in the performance of these estimators in low-data regimes, as well as identifying if there are any trade-offs between the two methods, and looking at specific examples of products that gain or lose significantly when moving from frequentist quality estimates to EB. We chose to use R to implement our experiments; all of the code and data for our experiments can be found at [https://github.com/LEFTA98/empirical_bayes], including code for generating the synthetic datasets.

For each of the datasets below, we split the users 60–40 into a train-test split. After training a prior using the training subset with the method described in Section 3, we carry out our analysis as follows: First, we filter out any products with fewer than 100 reviews, then cap any remaining products at exactly their 100 earliest reviews. We further split this set into a learning set and evaluation set, where the former contains the first 50 reviews for each test set product and the latter contains the last 50 reviews for each test set products. Let \( r_{i}^{\text{learn}} (r_{i}^{\text{eval}}) \) refer to the number of \( i \)-star reviews for product \( r \) in the learning set (evaluation set), and \( N_{r}^{\text{learn}} (N_{r}^{\text{eval}}) \) be the total number of reviews for product \( r \) in the learning set (evaluation set). While filtering out data with fewer than 100 data points seems counterintuitive to solving the cold start problem, we take this approach so that we have a reliable ground-truth estimate of what the quality of a product is through the evaluation dataset; we investigate cold-start in this context by limiting the number of ratings per user in the learning set the algorithm sees.

### 4.1 Datasets

We make use of a dataset of reviews for 71,982 products listed under the “Video Games” section on Amazon, sold on the platform from 1997 to 2018. We chose to use this dataset because of the quantity of this experiment we choose be a function of the true quality of the product. For the purposes of this experiment we choose \( \lambda = \frac{100}{\text{average rating}} \). This ensures that most products who are above-average quality will be above the 100-number cutoff for the test set, though there will be significantly less representation of lower-than-average products in our experiments; in practice, this should not change the distribution of ratings across products, but will significantly impact the availability of data for low-quality goods.

After splitting each dataset into train and test sets, we use the training data to fit a Dirichlet prior for each dataset, as per Section 3, filtering out from the training set any products with fewer than 20 reviews. Histograms of the average rating of each good in each dataset are shown in Figure 1 for products that have 20 or more reviews for different datasets. Note the heavy left-tailed skew for the Amazon dataset. Ratings for products in the scaled synthetic dataset were generated at a rate proportional to the true quality of the product. Note that this did not change the distribution of ratings of products in the scaled dataset compared to the uniformly generated synthetic dataset, though it does affect availability of ratings data for low-quality goods.

![Figure 1: Histograms showing distribution of average ratings of products with 20 or more reviews for different datasets. Note the heavy left-tailed skew for the Amazon dataset. Ratings for products in the scaled synthetic dataset were generated at a rate proportional to the true quality of the product. Note that this did not change the distribution of ratings of products in the scaled dataset compared to the uniformly generated synthetic dataset, though it does affect availability of ratings data for low-quality goods.](image)

### 4.2 Over-time comparison of EB and frequentist

The main advantage that we find the EB model to have over the frequentist approach is in how accurately it predicts the true quality of a product based on very few datapoints. We find that, when looking at the population-level mean-squared error, EB performs significantly better than the frequentist approach, with the largest gains being made in low-data regimes where there are few training examples for each product.
Our first experiment looks at how accurately the empirical Bayes posterior mean can estimate the true quality of a product when compared against the frequentist approach. We assume that for each product \( r \) in the test set of products, the proportion of \( i \)-star ratings it gets in the evaluation set is equivalent to the true probability parameter; that is, we assume \( p_{ir} = \frac{n_{ir}^{\text{eval}}}{N_{ir}^{\text{eval}}} \). For example, if 10 out of the 50 product reviews for product \( r \) in the evaluation set are 4-star reviews, we assume that the true probability that a review is 4 stars for \( r \) is \( \frac{1}{5} \). Given a set of estimators \( \{\hat{\theta}_{ir}\}_{i=1...5,r \in R} \), we define the mean-squared error to be \( \frac{1}{|R|} \sum_{r \in R} \sum_{i=1}^{5} (\hat{\theta}_{ir} - p_{ir})^2 \). Also of note for our later experiments will be the per-product mean-squared error, which is computed for a given product \( r \) and given by \( \sum_{i=1}^{5} (\hat{\theta}_{ir} - p_{ir})^2 \), and the estimated quality of a given product \( r \), calculated as \( \sum_{i=1}^{5} \hat{\theta}_{ir} \).

We compare the posterior mean calculated from equation (2) with the frequentist approach, which computes \( r_{i}^{\text{learn}} / N_{i}^{\text{learn}} \) as the estimate for the \( i \)-th event probability parameter for product \( r \) and does not use data from the training set. Figure 2 shows our observations of this comparison, where we vary the number of reviews that each product in the learning set gives to the model, ordered from oldest reviews first to newest reviews last. In all datasets, we see that our EB estimator achieves a lower mean-squared error than the frequentist approach at all learning window sizes, with the greatest improvements made when the number of training examples seen is low. In particular, the mean-squared error for EB dips below 0.1 for all datasets after seeing just 3 learning examples, compared to 12 learning examples for the frequentist approach on the Amazon dataset. Note the MSE for both estimates approach each other as the number of reviews increases; this fits the natural Bayesian intuition of the prior being overwhelmed by data as the number of learning examples increases.

Figure 2 shows the advantages of EB in cold-start scenarios: Empirical Bayes performs better than frequentist in low-data regimes. However, Empirical Bayes does not perform well across all products. This is seen in Figure 3, which plots the per-product mean squared error, stratified across the "true quality" of the product \( \sum_{i=1}^{5} n_{ir}^{\text{eval}} / N_r \). We observe that, in settings with few learning examples, EB gives good quality estimates for products with true ratings that were commonly present in the training data of the EB prior—in the case of the Amazon dataset, this value is roughly around 4 stars. However, products with true quality ratings that were not common in the population, such as 1-star products in the Amazon dataset, did better under the frequentist procedure when there were few learning examples. This suggests that the empirical Bayes estimator performs better on common products and does worse on outliers, while the frequentist estimator performs similarly on all products. Also of note are the results for the scaled dataset: Due to the lower number of ratings for low-quality goods, we have no information on products with a rounded quality score of less than 2, as many low-quality goods had an insufficient quantity of reviews to meet the test set cutoff of 100 reviews or more. This could imply an underrepresentation of low-quality goods in the Amazon dataset: if the true underlying data generation process for the Amazon dataset was dependent on the true quality of each product, as it was in the scaled dataset, then truly low-quality Amazon products would have less ratings and might not be included in fitting the EB algorithm.

4.3 Investigating individual products most impacted by empirical Bayes

In this subsection, we analyze individual products in the Amazon dataset with estimated qualities that differ the most when swapping out the frequentist approach for the EB estimator. Figure 4(a) shows the estimated quality, indexed by number of learning examples seen, for the product with the largest possible difference between its true average score and the frequentist approach’s estimated quality when using only one learning example. This particular product benefited greatly from EB, as it received many poor ratings early on, but gradually improved: When there were few data points, EB was willing to put more weight into the prediction that the product
Parametric Empirical Bayes for Predicting Quality in Rating Systems

Figure 3: Comparison of empirical Bayes versus frequentist quality estimation, stratified by true quality of the product, rounded to the nearest multiple of 0.5. The EB estimation error is lowest around the most common true quality scores for that dataset, but the frequentist approach beats EB on products with uncommon true quality scores relative to the population. The columns show the number of learning examples used.

Figure 4: Figures 4(a) (left) and 4(b) (right): Estimated quality of individual Amazon products indexed by number of learning examples. 4(a): the estimated quality of the product for which the one-datapoint frequentist estimator was furthest from the true average. 4(b): the estimated quality of the product for which the difference between the 50-datapoint EB estimator and ground truth was furthest off from the difference between the 50-datapoint frequentist estimator and ground truth. The straight line represents the true average, while the black dots represent individual ratings. EB does well for products that get bad ratings but improve over time, but for products with an uncommon true average, EB is eclipsed by frequentist estimation.

Conversely, Figure 4(b) shows a similar graph to 4(a), but for product that benefited the most after 50 learning examples from using the frequentist approach instead of EB. We quantify this by taking the good for which (difference between ground-truth, EB estimate) - (difference between ground-truth, frequentist estimate) was largest. This product received mostly 1-star reviews, though it had
a few good reviews at the beginning. Despite the overwhelmingly negative feedback from ratings, there were still enough 5-star ratings for this product so that the prior from empirical Bayes was still not overwhelmed after 50 learning examples. Note that our analysis from Section 4.2 suggests that there are far more items within the population that resemble the product in Figure 4(a), rather than the product in Figure 4(b). If this were not the case, then the fitted population prior would have instead had more probability mass towards lower-quality goods, meaning EB would have been more likely to believe goods were low-quality when operating off few datapoints, and so the EB estimate for Figure 4(b) would be lower. Figure 4 highlights a key limitation of our relatively simplistic EB model: Depending on which is more common in the underlying population, EB can either correct for products that ranked unusually low for their first few reviews, or for products that ranked unusually high for their first few reviews, but not for both at the same time.

5 FUTURE WORK

Many open directions remain from this study. EB could be used as an approach to model transfer learning in online marketplaces, where one tries to estimate the quality of a worker or product in a new market based on their past performance in previous market(s), such as in [12]. We believe, however, that the potential endogeneity of data generation mentioned in Section 4 is one of the most important aspects of this problem to work on. Because online platforms usually give highly-rated goods more exposure, it would be reasonable to assume that ratings are generated adaptively in response to the currently estimated quality of a product. If the product has a high estimated quality, it would be seen by more customers and hence garner more reviews; the opposite would be true for products with low estimated quality. As Figure 4(a) shows, EB offers one way for products that "unfairly" receive low reviews to maintain relatively accurate estimated quality even with few reviews, but endogeneity could still influence the overall EB estimation procedure. As experiments on the scaled dataset show, low-rated products could fall below the threshold to be included in the training or evaluation process, and even if they were included, the ratings from these products may not reflect that product’s true quality. In practice, a more sophisticated model would be dynamic: The platform creates a ratings system which induces certain types of products to get more ratings. These ratings then inform how the platform should update existing quality estimates for products. A ratings system that models this adaptive process would be invaluable if the end goal is real-world deployment, as a naive deployment of EB could suffer from the selection issues mentioned above.

6 CONCLUSION

In this paper we present an empirical Bayes framework for estimating the quality of products in an online marketplace. The key observation we made is that we could use data from multiple parallel data sources to create a more descriptive model for individual products in that data. Our empirical Bayes approach is relatively simplistic, addresses the cold-start problem of many ratings systems, and performs better in terms of mean-squared error than a baseline, frequentist approach. However, our procedure tends to do worse on uncommon products in the population moreso than in the frequentist method, and could be vulnerable to selection problems in how the underlying data for the problem is generated. More work needs to be done on how endogenous data generation impacts ratings systems.

REFERENCES

[1] [n.d.]. How star ratings work. https://www.uber.com/us/en/drive/basics/how-ratings-work/. Accessed: 2022-05-24.
[2] Hamus Bastani, Kimon Drakopoulos, Vishal Gupta, Ioannis Vlachogiannis, Christos Hadjicostisoulopolos, Pagona Lagidou, Giokas Magourikis, Dimitrios Paraukevis, and Sotiris Tsiouras. 2021. Efficient and targeted COVID-19 border testing via reinforcement learning. Nature 599, 7883 (2021), 108–113.
[3] Gary Bolton, Ben Greiner, and Axel Ockenfels. 2013. Engineering trust: recency in the production of reputation information. Management science 59, 2 (2013), 265–285.
[4] Luis Cabrall and Ali Hortacsu. 2010. The dynamics of seller reputation: Evidence from eBay. The Journal of Industrial Economics 58, 1 (2010), 54–78.
[5] Chrysanthos Dellarocas. 2003. The digitization of word of mouth: Promise and challenges of online feedback mechanisms. Management science 49, 10 (2003), 1407–1424.
[6] Bradley Efeon, Robert Tibshirani, John D Storey, and Virginia Tusher. 2001. Empirical Bayes analysis of a microarray experiment. Journal of the American statistical association 96, 456 (2001), 1151–1160.
[7] Snehalkumar (Neil) S Gaikwad, Durim Morina, Adam Ginzberg, Catherine Mullings, Shirish Goyal, Dariusz Gamage, Christopher Diemert, Mathias Burton, Sharon Zhou, Mark Whiting, et al. 2016. Boomerang: Rebounding the consequences of reputation feedback on crowdsourcing platforms. In Proceedings of the 29th Annual Symposium on User Interface Software and Technology. 625–637.
[8] Nikhil Garg and Ramesh Jhohari. 2019. Designing optimal binary rating systems. In The 22nd International Conference on Artificial Intelligence and Statistics. PMLR, 1930–1939.
[9] Nikhil Garg and Ramesh Jhohari. 2021. Designing informative rating systems: Evidence from an online labor market. Manufacturing & Service Operations Management 23, 3 (2021), 589–605.
[10] Jonathan Huang, 2005. Maximum likelihood estimation of Dirichlet distribution parameters. CMU Technique Report (2005), 1–9.
[11] Nikolaos Ignatias and Stefan Wager. 2019. Covariate-powered empirical Bayes estimation. Advances in Neural Information Processing Systems 32 (2019).
[12] Marios Kokkodis and Panagiotis G Ipeirotis. 2015. Reputation Transferability in Online Labor Markets. (2015).
[13] Benjamin Marlin. 2004. Collaborative filtering: A machine learning perspective. University of Toronto.
[14] Carl N Morris. 1983. Parametric empirical Bayes inference: theory and applications. Journal of the American statistical Association 78, 381 (1983), 47–55.
[15] Jianman Ni. [n.d.]. Amazon Review Data (2018). https://nijianman.github.io/amazon/index.html. Accessed: 2022-02-18.
[16] Amanda Pallais. 2014. Inefficient hiring in entry-level labor markets. American Economic Review 104, 11 (2014), 5565–5599.
[17] Herbert Robbins. 1964. The empirical Bayes approach to statistical decision problems. The Annals of Mathematical Statistics 35, 1 (1964), 1–20.
[18] Herbert E Robbins. 1992. An empirical Bayes approach to statistics. In Breakthroughs in statistics. Springer, 388–394.
[19] Matthew J Salganik, Peter Sheridan Dodds, and Duncan J Watts. 2006. Experimental study of inequality and unpredictability in an artificial cultural market. Science 311, 5762 (2006), 854–856.