Quantifying and predicting success in show business

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Abstract. Recent studies in the science of success have shown that the highest-impact works of scientists or artists happen randomly and uniformly over the individual’s career. Yet in certain artistic endeavours, such as acting in films and TV, having a job is perhaps the most important achievement: success is simply making a living. By analysing a large online database of information related to films and television we are able to study the success of those working in the entertainment industry. We first support our initial claim, finding that two in three actors are “one-hit wonders”. In addition we find that, in agreement with previous works, activity is clustered in hot streaks, and the percentage of careers where individuals are active is unpredictable. However, we also discover that productivity in show business has a range of distinctive features, which are predictable. We unveil the presence of a rich-get-richer mechanism underlying the assignment of jobs, with a Zipf law emerging for total productivity. We find that productivity tends to be highest at the beginning of a career and that the location of the “annus mirabilis” – the most productive year of an actor – can indeed be predicted. Based on these stylized signatures we then develop a machine learning method which predicts, with up to 85% accuracy, whether the annus mirabilis of an actor has yet passed or if better days are still to come. Finally, our analysis is performed on both actors and actresses separately, and we reveal measurable and statistically significant differences between these two groups across different metrics, thereby providing compelling evidence of gender bias in show business.

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1 Introduction

“It’s feast or famine in showbiz.” - Joan Rivers. A sentiment likely to be echoed by many would-be stars of the silver screen. But for those that feast the rewards are, at least thought to be, worth the risk. The so-called science of success has recently uncovered many features of the careers of academics (1), artists (2), and all manner of other individuals whose output can be effectively assessed over the course of their working life (3–5). In the world of scientific research it has revealed the unpredictability of the timing of an academics most impactful work (1), showing that even such prestigious awards as Nobel prizes are randomly distributed throughout the career of a scientist. The anatomy of funding and collaborations in universities has revealed “rich clubs” of leading institutions, and suggested that such patterns of collaborations contribute greatly to the success of these institutions, as measured in terms of over-attraction of available resources and of breadth and depth of their research products (6). Studies of innovation in industry across different countries have found that the commercial success of manufacturing plants is far more closely related to intra-group links than external ties (7). Strikingly, these features can be common across multiple areas; the Matthew effect (8, 9), or the rich get richer phenomenon, and the recently discovered presence of “hot streaks” (10), are not restricted to isolated cases. With regards to success, a great deal of work has been done in assessing impact (1, 11), the distribution of standout or landmark works (12, 13), whether these are related to the age of the individual in question (14, 15), how impact can be assessed in the long term (16), and even prediction of future successes (17, 18). Indeed the fortunes of both films and the actors and actresses that make them have been studied in some specific ways (16, 19–21). These studies do not however address the question that interests those who are not already on the higher rungs of the ladder of success: how can one avoid the famine and build a sustainable career in acting?

The aim of this work is to use a data-driven approach in order to define, quantify and even predict the success of actors and actresses in terms of their ability to maintain a steady flow of jobs. Drawing on the International Movie Database (IMDb), an online database of information related to films, television programs and home videos (22), we have been able to study the careers of millions of actors from several countries worldwide, from the birth of film in 1888 up to the present day. Each career is viewed as a profile sequence: the yearly time series of acting jobs in films or TV series over the entire working life of the actor or actress. Note that all acting jobs are considered, regardless of salary, role, screen time, or the impact of the work. The statistical analysis of such a large number of profile sequences allows us to derive some general properties of the actors activity patterns. In particular, we have looked at several quantities of interest such as career length, productivity (defined as the number of credit jobs in a year or in the entire career of an actor) and position of the annus mirabilis, defined as the year with the largest number of credited jobs. We have also explored possible emergence of gender inequality in these properties.

The first message that emerges from our quantitative analysis is that one-hit wonders, i.e. actors whose career spans only a single year, are the norm rather than the exception. Long career lengths and high activity are found to be exponentially rare, suggesting a scarcity of resources in the acting world. We also see that that this scarcity unequally applies to actors and actresses, providing compelling evidence of gender bias. Moreover, the total productivity of an actor’s career is found to be power-law distributed, with most actors having very few jobs, while a few of them have more than a hundred.
This indicates a rich-get-richer mechanism underlying the dynamics of job assignation, with already scarce resources being allocated in a heterogeneous way. All of this suggests that it is activity that is truly important when measuring success in show business. Only a select few will ever be awarded an Oscar, or have their hands on the walk of fame, but this is not important to the majority of actors and actresses who simply want to make a living. It is the continued ability to work, as opposed to prestige which is most likely to ensure a stable career. For these reasons we propose that predictions of success in show business should be focused on activity and productivity.

Motivated by these results, we then address the questions that interest the majority of working actors and actresses. Questions such as “am I going to get another paid job?” or “is this year going to be my best?”. We first show that efficiency, defined as the ratio between the total number of active years and the career length, is unpredictable, as there is no evident correlation between these two things. This is in line with recent studies (1, 10) pointing out that the most impactful pieces of work across artistic and scientific disciplines usually happen randomly and uniformly over an individual’s career, and accordingly such achievements are unpredictable. Nevertheless, we here, surprisingly, find distinctive features in their temporal arrangement. In particular, we find that actor careers are clustered in periods of high activity (hot streaks) combined with periods of latency (cold streaks). Moreover, we discover that the most productive year (annus mirabilis) for both actors and actresses is located towards the beginning of their career, and that there are clear signals preceding and following the location of the annus mirabilis of an individual. Altogether, these unexpected results lead us to conclude that prediction is possible in theory. Finally, we validate this hypothesis by building a statistical learning model which predicts the location of the most productive year, finding that we can, with up to 85% accuracy, tell whether an actor’s career has reached its most productive year yet or not.

2 Results

We study the careers of 1,512,472 actors and 896,029 actresses as recorded on IMDb as of January 16th, 2016, including careers stretching back to the first recorded movie in 1888. The career of each actor \( a \) is characterised by his/her track record, which consists of a set of pairs of numbers representing respectively each year when actor \( a \) was credited in IMDb, and the number of different credits in that year. As credits we count the number of acting jobs in films and/or TV series. A sketch of the typical activity pattern of an actor is reported in Figure 1, showing the yearly credits from the first to the last year of thir career. Notice that there are not only active years, where the actor has credited jobs in IMDb, but also latent years with no recorded jobs. We therefore fill the latent years with zeros and construct the profile sequence \( \{ w_k \}_{k=1}^L \) of each actor \( a \) as depicted in the top part of Figure 1. The quantity \( w_k \) denotes the actor’s local productivity in year \( k \), i.e. the number of credited jobs in that year. The length of an actor’s career is defined as the number of years between the first and the last active year (inclusive), and is denoted as \( L \). The total number of active years \( s \) is from now on referred to as the activity of an actor. Since a career can have latent years intertwined with active ones we must have \( s \leq L \), moreover \( L - s \) is the number of latent years. By definition we have: (i) \( L \geq 1 \), (ii) \( s \geq 1 \) and (iii) \( s = 1 \Leftrightarrow L = 1 \).

Finally, we define the total productivity \( n \) of an actor, as the cumulated number of credited jobs, \( n = \sum_{k=1}^L w_k \). The annus mirabilis (AM) of a given actor is defined as the year where the actor was credited with the largest number of works in IMDb: \( AM = m \), where \( m \) is such that \( w_m = \)}
Figure 1: **Career activity pattern of an actor.** The yearly productivity of a given actor, measured as the total number of IMDb credited jobs in each year, is reported from the first to the last year of the actor activity. Shown is the case of an actor whose career spanned $L = 23$ years and who was credited a cumulated $n = 17$ different jobs in $s = 12$ years. From the yearly productivity we can construct the actor profile sequence $w_k$, with $k = 1, \ldots, L$, shown in brackets above the plot, which can be modelled as a stochastic marked point process.

$$\max\{w_k\}_{k=1}^L.$$ In the case that this $m$ is not unique we take the final such year: $AM = \max\{m\}$.

### 2.1 Career lengths and one-hit wonders

We start our analysis by exploring the statistics of the career length $L$. In panel (a) of Figure 2 we plot in a semi-log scale the empirical distribution of career lengths $P(L)$, for both actors and actresses finding that the tail is well fitted by an exponential distribution. By construction, $P(L = 1) = P(s = 1)$ and this quantity represent the percentage of one-hit wonders i.e. of actors whose career started and ended, according to IMDb, in the same year. Interestingly, we find that the percentage of such cases is extremely high (around 69% for males and 68% for females) and deviates from the otherwise decaying exponential distribution. This sharp deviation highlights that one-hit wonders are not an exception in show business, but, on the contrary, are the norm. A zoom of the distribution in the range $L \in [2, 10]$ is reported in the inset of (a), revealing systematic differences between actors and actresses, suggesting that it is consistently more common to find (non-one-hit wonder) actresses with shorter career lengths than actors. We have indeed performed a model selection experiment which confirms that gender bias is statistically significant (see SI for details).

The empirical probability distribution of activities, displaying the probability of sampling an actor that worked in $s$ years, is shown in panel (b) of Figure 2 in a semi-log scale. Most of the actors and actresses are only active in a single year ($s = 1$), as by default $s = 1 \mapsto L = 1$. The probability of finding actors with large activity, i.e. those that have worked in many different years, decays exponentially fast. This exponential decay mimics the similar decay in the probability of finding long
Figure 2: **Career length, activity and productivity distributions.** (a) The probability $P(L)$ that an actor or an actress has a career of length $L$, estimated by computing the frequency histogram of the number of years between the first and the last recorded entry on IMDb. $P(1)$ measures the abundance of “one-hit wonders”, namely the actors or actresses with IMDb records in a single year. A zoom for $L \in [2, 10]$ in the inset shows that careers extending between 2 and 10 years are proportionally more frequent in women than in men. (b) Activity distribution $P(s)$ estimated by computing the frequency histogram of the number of working years within each career ($s \leq L$). Curves for actors and actresses are very similar and both exhibit a clear exponential tail, implying a ‘scarcity of resources’. (c) Log-log plot of the total productivity distributions $P(n)$ for actors (black) and actresses (blue). Both curves decay as a power law $P(n) \sim n^{-\gamma}$, where $\gamma \approx 2$, revealing a Zipf law for the total number of acting jobs.

career lengths and altogether are the basis for claiming a *scarcity of resources* in show business, i.e. there are many more actors/actresses than job offers (23). This lack of resources naturally leads to a question: how are they allocated? We address this question in the next section.

### 2.2 Productivity and the rich gets richer phenomenon

The right panel of figure 2 shows the empirical distributions of total productivity $P(n)$, reporting the normalized numbers of actors or actresses with $n$ appearances in movies or TV series over their careers. While the career length distribution $P(L)$ and the activity distributions $P(s)$ are well fitted in their tails by an exponential law, $P(n)$ decays more slowly and can be fitted by a power law $P(n) \sim n^{-\gamma}$ with exponent $\gamma \approx 2$. This emergence of a power law shape in the distribution of total productivity implies that another scaling function emerges when the statistics are computed in a rank-frequency plot. It is indeed well known (24) that observing a power law distribution with exponent $\gamma$ for the abundance of some variable is equivalent to obtaining a power law scaling for the frequency of the variable that appears with rank $r$: $f(r) \sim r^{-\alpha}$, where both scaling laws are mathematically related via $\alpha = 1/\left(\gamma - 1\right)$. The celebrated Zipf law refers to the particular case $\alpha \approx 1$, which is indeed the case here. The fact that a Zipf law emerges for the rank-frequency distribution of the total productivity of an actor may suggest a mechanistic explanation for our observations. Many different proposals for the mechanism underpinning the emergence of a Zipf law, and several names for the phenomenon itself, have been put forward in various contexts, including the Simon-Yule process, the mechanism of preferential attachment, the Matthew effect, the Gibrat principle, rich-get-richer, etc. In this context, inspired by the renowned preferential attachment paradigm as a generative model
to produce scale-free networks, we can easily explain the onset of a power law distribution for the
total productivity in terms of a rich-get-richer heuristic: consider a generative model of an actor’s
network, where nodes are actors and two actors are linked if they act in the same film. Initially
only a few actors are working, but as time goes on new actors come into play. In this a way the
new individuals work in films together with other actors with a probability which is proportional
to the total productivity (i.e. the total number of links) of the older actor-node. This preferential
attachment clearly expresses the rich-get-richer phenomenon by which actors that work a lot will
have a higher chance of working even more than actors with low productivity. It is well known that
such models generate networks with power law degree distributions (25–28), i.e. power laws for the
total productivity. This result is not at all unexpected, after all, the more well-known someone is, the
more likely producers will be to put him or her in their next film, if only for commercial purposes.
What is perhaps dramatic about this observation is that it is well known that rich-get-richer effects are
rather arbitrary and unpredictable, as large hubs can evolve out of unpredictable and random initial
fluctuations which have been amplified, and not based on any particular intrinsic fitness (28) (such as
acting skills). Quoting Easley and Kleinberg: “if we could roll time back 15 years, and then run history
forward again, would the Harry Potter books again sell hundreds of millions of copies, or would they
languish in obscurity while some other works of children’s fiction achieved major success?”. As
a matter of fact, it seems likely that across different parallel universes popularity would still have
a power law distribution, but it is far from clear that the most popular actors would always be the
same. Interestingly, this hypothesis has recently been validated in an online social experiment for the
case of musical popularity (29). In summary, productivity is probably the variable every actor aims
to maximise, but these results suggest that boosting this is more of a network effect (30, 31) than a
consequence of ‘acting skills’.

2.3 Efficiency is unpredictable

In figure 2 we observed that career length and activity are variables which are both exponentially
distributed, indicating a scarcity of resources. In this section we further explore whether the two
quantities \( L \) and \( s \) are correlated. We first define an actor’s efficiency as the ratio \( \frac{s}{L} \) of active years
over the entire career, and we investigate how this efficiency is distributed. By construction, we have
\( s \leq L \) and \( L = 1 \rightarrow s = 1 \), and thus in this case \( \frac{s}{L} = 1 \). As roughly 68% of actors are one-hit-
wonders, we expect that the probability that an actor has optimal efficiency \( P\left(\frac{s}{L} = 1\right) \) \( \approx P\left(L = 1\right) \).
However it is clear that these are ‘pathological’ cases as efficiency is not really well defined for one-
hit wonders. In what follows, we therefore assume that the case \((s = 1, L = 1)\) is an outlier with
regards to the analysis of efficiency.

In Figure 3 we plot \( P\left(\frac{s}{L}\right) \) on semi-log axes for actors (top panel) and actresses (bottom panel). As
might be expected, the distribution decreases rapidly as \( \frac{s}{L} \) approaches either zero or one, suggesting
that most actors and actresses have intermediate values of efficiency (see SI for a discussion and a
heuristic explanation of this phenomenon). The shape of \( P\left(\frac{s}{L}\right) \) in the intermediate range is fractal-
like, which is due to the fact that \( s \) and \( L \) are (small) integers and thus \( \frac{s}{L} \) cannot take arbitrary
values in \([0,1]\). The fractal shape can actually be related to the density of irreducible fractions over
the integers, as depicted in the bottom panel of Figure 3, and is not a property linked to the relation
between \( s \) and \( L \). In other words, when this effect is factored out, then \( P\left(\frac{s}{L}\right) \) is essentially flat in the
intermediate range. Accordingly, correlations that emerge between the activity $s$ and the career length $L$ of an actor at intermediate ranges seem to be related only to the fact that $s \leq L$. To further validate this hypothesis, we performed a scatter plot of $s$ versus $L$ for all actors and actresses, and computed the Pearson correlation coefficient. This was then compared to the correlation coefficient of a null model generated by randomly extracting values of $L$ and $s$ from the pool of career profiles, ensuring that $L \geq s$. For actors, we found that $s$ and $L$ correlate with a Pearson coefficient $r \approx 0.67$, whereas in the null model we obtained $r_{\text{null}} \approx 0.54$ (in the case of actresses $r \approx 0.67$, to be compared with $r_{\text{null}} \approx 0.56$). As expected, $s$ and $L$ are indeed correlated but almost all of those correlations can be explained by a null model, concluding that for intermediate ranges there are in practice not strongly influential additional correlations between length and activity: the activity of an actor cannot be predicted by their career length and therefore we can conclude that the efficiency is an unpredictable quantity.

2.4 **Actors careers are clustered in hot and cold streaks**

To understand the *temporal* arrangement of active years within the profile sequence of a given actor, we now consider the statistics of waiting times. A waiting time $\tau$ is defined as the time elapsed (in
years) between two active years (equivalently, a waiting time is a collection of successive latent years), and its statistics provide a classical way to analyse the presence of memory and bursts in time series (32, 33). We have estimated the waiting time distribution $P(\tau)$ for actors and actresses, discarding those with short career lengths, $L < 10$ years, to avoid a lack of statistics. To estimate this distribution, for each actor (actress) we count how frequently one observes waiting times of a certain duration $\tau$, and normalize the accumulated frequencies. This process will inevitably introduce finite size biases since, for short career lengths, we are more likely to find short waiting times, simply because there is no room for long ones. For a proper comparison we therefore have also computed the distribution for a randomized null model $P_{null}(\tau)$ where all of the profile sequences have been shuffled (while keeping the first event $w_1$ and the last event $w_L$ unaltered). A lack of temporal correlations would imply $P_{null}(\tau) = P(\tau)$, whereas systematic differences suggest the onset of temporal correlations in the activity of actors. In panel (a) of Figure 4 we report the difference $P(\tau) - P_{null}(\tau)$ as a function of $\tau$. For both actors and actresses, we systematically find $P_{null}(\tau = 1) < P(\tau = 1)$, and $P_{null}(\tau > 1) > P(\tau > 1)$, that is, active years are more clustered than they would be by chance, and hence the same is true of periods of inactivity. This means that the profile sequence shows clustering and is composed of bursts of activity (hot streaks) where actors and actresses are more likely, than would be expected by chance, to work in a year if they worked the year before ($\tau = 1$). This result is in agreement with recent findings in other creative jobs in science and art (10). Additionally, these hot streaks are interspersed by abnormally long periods of latency (cold streaks) where authors are less likely than random to work in a given year if they did not work the year before ($\tau > 1$).

Furthermore, to appropriately compare deviations from the null model for different waiting times, in panel (b) of Figure 4, we plot the relative difference (in percentage) $[P(\tau) - P_{null}(\tau)] \cdot 100/P_{null}(\tau)$. We find a substantial difference between actors and actresses: while deviation from the null model decays for larger waiting times $\tau$ in the case of actors, for actresses this relative deviation is maintained, pointing to a longer memory kernel, in turn suggesting that having a period of latency is overall more detrimental for actresses than for actors.
2.5 Predicting the annus mirabilis

It has recently been found that the most impactful publication that a scientist will produce is equally likely to occur at any stage of their career (I). Here we explore a related question in the context of actors and actresses. Instead of impact, the indicator of success under study is productivity, as measured by the number of credited works in IMDb. We concentrate on actors and actresses with working lives extending beyond $L = 20$ years, and define the annus mirabilis (AM) of a given actor as the year $k = y^*$ when the actor worked in the largest number of credited movies or TV series. We restrict our reported results to those cases where there were at least 5 credited jobs in the AM, although other thresholds do produce qualitatively similar results. The subset of actors with $L > 20$ and more than 5 acting jobs in the AM consists of 15357 actors (1.02%) and 5904 actresses (0.65%). The large gender difference indicates that actors tend to have more acting jobs than actresses.

In Figure 5 we plot the probability with which the AM will occur at each point within an actor or actress’s career. To be able to compare these probabilities over careers of varying lengths, we have broken up each actor’s time series of $L$ years respectively into 5 bins (other segmentations produce qualitatively similar results). The plots consistently indicate that the most probable location of the annus mirabilis is towards the beginning of a career. Although the results are qualitatively similar for male and female actors, this bias is much more pronounced in the case of actresses, further confirming the gender difference previously observed.

To study whether one can detect the imminent appearance of an actor’s annus mirabilis we have analysed, for both actors and actresses, the average number of acting jobs before and after the AM. In order to do this consistently, we initially perform a translation $k \mapsto \kappa$ that aligns all profile sequences, so that the annus mirabilis $k = y^*$ all occur at $\kappa = 0$. We then define:

$$\xi(\kappa) = \frac{1}{|A|} \sum_{i=1}^{|A|} w_i(k + \kappa),$$

where $\kappa$ is the offset from the annus mirabilis and $|A|$ is the size of the set of actors/actresses for which there exists a profile sequence with an input at offset $\kappa$. In Figure 6 we plot $\xi(\kappa)$, showing that,
on average, there is a clear increase in the number of jobs preceding the AM and a clear decrease immediately afterward. This pattern is absent in the corresponding null models obtained by shuffling the profile sequences (red bars). Such observed patterns can indeed be exploited for an early prediction of the annus mirabilis.

Figure 6: **The annus mirabilis is predictable.** The total number of acting jobs, $\xi(\kappa)$, averaged over all actors (left panel) and actresses (right panel), is reported as a function of the number of years $\kappa$ after or before the annus mirabilis. Only actors and actresses with a career lasting more than $L = 20$ years and annus mirabilis with $w > 5$ acting jobs have been selected. In both cases, we observe a clear non-monotonic pattern, indicating that the annus mirabilis is either approaching or has just passed. For comparison, we report in red the results obtained for a null model where the profile sequences of all actors and actresses have been shuffled. No pattern emerges in that case.

Based on our observed distribution of jobs surrounding the annus mirabilis we propose a naive early-warning criterion: if the career sequence is non-monotonic around a value of $k$, i.e. if $w_k > w_{k-1}$ and $w_{k+1} < w_k$, then the year $k$ is a good candidate for the annus mirabilis. With this criterion in mind, one could ask the following question: given a sample of an actor or actress’s profile sequence, can we tell whether the annus mirabilis has already passed or not? Mathematically, the question above can be formalised as follows: given a career sequence $(w_k)_{k=1}^L$ such that the maximal total productivity occurs at time $k = y^*$, consider a truncated sequence $\bar{w}_k = (w_k)_{k=1}^T$. We now wish to know if we can accurately assess whether $y^* \in \{1, ..., T\}$ using only $\bar{w}_k$. This forms a binary classification problem, in which $\bar{w}_k \in C_1$ if $y^* \notin \{1, ..., T\}$ and $\bar{w}_k \in C_2$ otherwise. Our naive criterion, as illustrated above, readily provides the heuristic: $\bar{w}_k \in C_1$ if $\bar{w}_k$ is monotonic, and $\bar{w}_k \in C_2$ if not. When this method is tested on an appropriately generated set $\mathcal{W}$ of truncated sequences (see SI for details) we find that it is correct $\sim 69.2\%$ of the times for actors, and $\sim 75.0\%$ of the times for actresses. This model now forms a benchmark against which we will test a more refined approach. The idea is to relax our classification method by introducing some parameters which allow for deviation from the rigid heuristic, then train those parameters on some subset $\mathcal{T} \subseteq \mathcal{W}$, and subsequently test the trained model on the test set $\mathcal{W} \setminus \mathcal{T}$. To do this let us first define the function

$$D(\bar{w}_k) = - \sum_{y=1}^{T-1} \min(0, \bar{w}_{y+1} - \bar{w}_y).$$  \hspace{1cm} (1)$$

At each year $k$ the contribution to $D$ from that year is zero if the total productivity in the subsequent year is larger. This means that for a monotonically increasing sequence $\bar{w}_k$, $D(\bar{w}_k) = 0$. If productivity decreases from year $k$ to $k+1$, then $D$ will increase by a corresponding amount.
Table 1: Performance metrics (accuracy, precision, recall and F1 score) of the proposed classification method for the prediction of the annus mirabilis.

| Quantity | Actors | Actresses |
|----------|--------|-----------|
| Total $C_1$ | 44652 | 16145 |
| Total $C_2$ | 57553 | 29275 |
| Accuracy | 0.8405 | 0.8637 |
| Precision | 0.8608 | 0.8287 |
| Recall | 0.7575 | 0.7773 |
| F1 score | 0.8058 | 0.8021 |

$D(\tilde{w}_k)$ effectively measures how far the sequence $\tilde{w}_k$ is from being monotonically increasing, thus we can use it to relax our naive heuristic by defining some threshold $d$ such that the decision rule $C(\tilde{w}_k, d)$ becomes

$$C(\tilde{w}_k, d) = \begin{cases} C_1 & \text{if } D(\tilde{w}_k) < d \\ C_2 & \text{if } D(\tilde{w}_k) \geq d. \end{cases}$$

This new classifier is more flexible than the naive heuristic as we have introduced a parameter $d$ which can now be optimised (trained) as follows: if we denote $C^*(\tilde{w}_k)$ as the true class of the sequence $\tilde{w}_k$, then the optimal value of the parameter $d^*$ is the value of $d$ that minimises the following loss function

$$L(T, d) = -\sum_T \delta(C(\tilde{w}_k, d), C^*(\tilde{w}_k)). \quad (2)$$

Where $\delta(X, Y)$ yields one if $X = Y$ and 0 otherwise. This value for $d^*$ is then used to classify the remaining sequences in $W \setminus T$. The results of this testing on both actors and actresses can be partially summarised by the two confusion matrices $CO_m$ (for actors) and $CO_f$ (for actresses):

$$CO_m = \begin{bmatrix} 33775 & 5659 \\ 10771 & 52000 \end{bmatrix}, \quad CO_f = \begin{bmatrix} 12549 & 2593 \\ 3596 & 26682 \end{bmatrix}$$

The classical metrics used to assess the performance of the classifier, namely accuracy, precision, recall and the F1 score, are summarised in Table 1. We find that the accuracies of the prediction are 84% and 86% respectively, i.e. $\sim 10\%$ higher than those obtained using a naive heuristic.

### 3 Discussion

In this work we have made use of the vast quantity of data presented by IMDb to explore, analyse and predict success on the silver screen. By studying the careers of 1,512,472 actors and 896,029 actresses from 1888 up to 2016, we have uncovered a number of distinctive patterns that characterize various aspects of the film and TV industries. Such patterns not only allow us to identify qualities of individual actors or actresses working lives, but also to gain a deeper insight into the mechanisms by which jobs are themselves assigned. Based on our findings, we have then constructed a statistical learning model that predicts with high accuracy whether an actor or actress is likely to have a bright future, or if the best days are, unfortunately, behind them.
The analysis performed in the first part of our work supports the following eight key observations: (i) One-hit wonders are the norm, rather than the exception. This implies that productivity is probably a variable more closely related to success, rather than the importance or impact of particular jobs. (ii) Resources are scarce: long careers and higher activities are exponentially rare, implying that there are far fewer jobs available than there are applicants. (iii) A rich-get-richer mechanism underlies the way jobs are assigned, as evidenced by the emergence of Zipf’s law in the distribution of both actors and actresses total number of credited works. This fact suggests (29) that high productivity is likely to be a network effect (30, 31) rather than purely based on merit, i.e. productivity does not necessarily correlate with acting skills. (iv) The efficiency of an actor (the ratio between active years and length career) is unpredictable, a finding reminiscent of the randomness discovered in (1). (v) Careers are clustered in periods of high activity or “hot-streaks” (again in agreement with recent findings (10)) interspersed with periods of latency (cold streaks), an effect which is more pronounced for actresses. (vi) The most productive years for both actors and actresses tend to be towards the start of their careers though, again, this is more evident for actresses. Again, we see here evidence for gender bias: older actresses are far less likely to maintain their status in the acting world than men. (vii) There are clear signals both preceding and following the most productive years of an actor or actresses career. (viii) Including the aforementioned points, we have found statistically significant differences between actors and actresses across a wide range of metrics, providing credible and convincing evidence of gender bias.

The second part of our work deals with the prediction of an actors productivity. By utilising the observed patterns present across the careers of both actors and actresses we have produced a statistical learning model which, given a sample of a career, is able to predict with roughly 85% accuracy whether that career has peaked, or whether there are better things in store for our budding star.

To conclude, a life in show business appears to be very different to those of artists or scientists. Where recent works have found an inherent unpredictability and randomness in the careers of academics and creatives we have found predictability and patterns. It is now natural to ask why these differences occur; why were we able predict the fortunes of individuals in one area while it has been shown to be impossible to do so elsewhere? Another natural and intriguing problem to investigate might be the following: suppose we have predicted that a certain actors annus mirabilis has passed. What then can the actor do to change their fortunes and bring about even greater success? We hope that our methodology and the results that we have obtained will contribute to the ongoing debate surrounding the science of success (30). Given the scope of our findings across the industry, we also wish that our work will be of interest to those working within it.

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Author contributions

LL, VL and OW designed the study. OW and LL performed the data analysis. All authors interpreted results and wrote the paper.

Author declaration

The authors declare no conflicts of interest.

Supplementary materials

Supplementary Text
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