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Invasion biology and the success of social collaboration networks, with application to Wikipedia

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We adapt methods from the stochastic theory of invasions – for which a key question is whether a propagule will grow to an established population or fail – to show how monitoring early participation in a social collaboration network allows prediction of success. Social collaboration networks have become ubiquitous and can now be found in widely diverse situations. However, there are currently no methods to predict whether a social collaboration network will succeed or not, where success is defined as growing to a specified number of active participants before falling to zero active participants. We illustrate a suitable methodology with Wikipedia. In general, wikis are web-based software that allows collaborative efforts in which all viewers of a page can edit its contents online, thus encouraging cooperative efforts on text and hypertext. The English language Wikipedia is one of the most spectacular successes, but not all wikis succeed and there have been some major failures. Using these new methods, we derive detailed predictions for the English language Wikipedia and in summary for more than 250 other language Wikipedias. We thus show how ideas from population biology can inform aspects of technology in new and insightful ways.

Keywords: invasion biology; stochastic population theory; social collaboration networks; Wikipedia

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Introduction

It is difficult to overestimate the effect that Charles Elton’s book *The Ecology of Invasions by Animals and*

Plants (1958) had on population biology. It remained the most highly cited source on the subject 50 years after its publication (Richardson & Pysek 2008). Although invasion biology covers a wide intellectual swath, one of the fundamental questions concerning invasions is whether a founding population of a certain size will establish itself or fail – that is, will the descendants of the initial propagule(s) reach a level considered to be self-maintaining or fall back to 0? Stochastic population theory is used to answer this question (MacArthur & Wilson 1967; Mangel 2006).

Social collaboration networks have become ubiquitous (Newman 2010; Easley & Klineberg 2011) and when such a network is started, one can envision it as a propagule of users ‘invading’ the worldwide web. Understanding whether a social collaboration network will succeed or fail is a problem with wide interest, with applications that range from investment in social media, to monitoring terrorist networks, to science education (e.g. Micklos et al. 2011), but we currently lack methods to make predictions of success. In this paper, we use methods from stochastic population theory (Mangel & Ludwig 1977; Mangel 1994; Mangel 2006) to show how such a prediction can be made. Population biologists will find our approach familiar, but with a new application and connection to the world of technology. Technologists interested in social networks will find novel features that include: (1) characterizing the stochastic growth of a social collaboration network; (2) a clear definition of success in terms

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of reaching a specified number of active users before falling to 0 [or any other low number] of active users; (3) derivation and solution of the differential equation characterizing the probability of success; (4) application of Maximum Likelihood Estimation (MLE) and the Akaike Information Criterion (AIC) to determine parameters and then weight possible models of success given data on participation; and (5) application of Markov Chain Monte Carlo (MCMC) methods to determine the distribution of parameters for each potential model. We mainly focus on the English language Wikipedia, but consider the remaining 250+ languages in the supplemental information (SI) (supplemental material is available online). In summary, we show a novel and important interdisciplinary approach that is broadly applicable.

About wikis

A wiki is a website in which multiple, dispersed participants create and edit interlinked web pages (Ebersbach et al. 2008; Mader 2008). One of the most famous wikis is Wikipedia, an online encyclopedia in more than 250 different languages, which has had remarkable success. Indeed, when viewed backwards across the time scale of a decade, the success of the English language Wikipedia (henceforth Wikipedia), measured by the number of individuals actively creating and editing pages (henceforth editors), seems to have been inevitable (Figure 1a). However, early on, the growth of Wikipedia shows fluctuations (Figure 1b) and the monthly change in the number of editors was sometimes very negative (Figure 1c).

Not all wikis succeed, and some of them – including those created by the *Los Angeles Times*, the Penguin publishing company and Amazon.com – were very short-lived (Mader 2008). Because wikis and other social collaboration networks are important in many fields, it is vital to ask how we can predict the success of a social collaboration network given early data, such as that shown in Figures 1(b) and 1(c). Although wikis can be of many types, we use Wikipedia as a case study.

In light of the fluctuations in the number of editors, the predicted success of a wiki must be a probabilistic quantity. Thus, our goal becomes computing the probability $u(w)$ that a wiki currently with w editors (the w indicating that individuals are writing and editing web pages) reaches a specified upper threshold w_u in which it is considered to be established before it falls to 0 editors.

Methods

In order to keep technical details to a minimum, we have put most of them in the Appendix, but there are some details that cannot be skimmed over. To capture the dynamics shown in Figure 1 requires a model that is both nonlinear (because of the sigmoidal shape) and stochastic (because of the fluctuations). We let $W(t)$ denote number of editors at time t and $dW = W(t+dt) - W(t)$. The entire trajectory in Figure 1(a) could then be

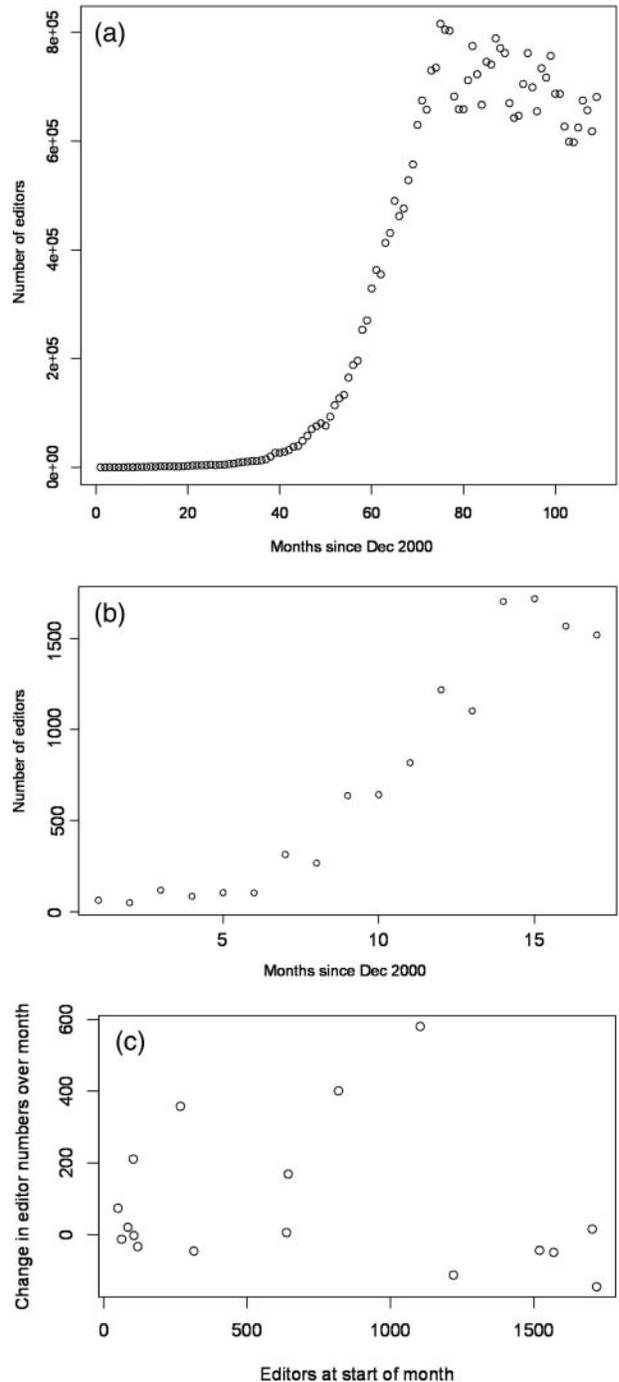


Figure 1. (a) When viewed backwards across about a decade, the growth of the English language Wikipedia seems inevitable, rising exponentially then saturating. (b) Early on, however, the number of active editors shows growth but considerable fluctuations. (c) When those data are converted to monthly change as a function of the current number of editors, large fluctuations can occur even when the number of editors is considerable.

described by a stochastic differential equation of the form (Schuss 1980):

$$dW = r(W)dt + \sigma(W)dB \quad (1)$$

where $r(W)$ and $\sigma(W)$ are functions of the number of editors, which have to be determined, and dB is an increment

in Brownian motion: it is normally distributed with mean 0 and variance $dt + o(dt)$, where $o(dt)$ denotes terms that are higher powers of dt .

For the analogy with a biological invasion, we assume that the number of editors is small, so that ‘density dependent’ effects that lead to the sigmoidal growth can be ignored. We then Taylor-expand the functions on the right-hand side of Equation (1), keeping only the linear terms to obtain

$$dW = (r_0 + r_1 W)dt + (\sigma_0 + \sigma_1 W)dB \quad (2)$$

where r_0, r_1, σ_0 and σ_1 are constants to be determined. As these constants vary, we have many possible models, depending upon which of these parameters is set equal to 0. In the absence of fluctuations (i.e. the second term on the right-hand side is set equal to 0), when $r_1 > 0$, Equation (2) corresponds to $W = 0$ being an unstable steady state and will lead to exponential-like growth in the number of editors. By setting some of the parameters in Equation (2) equal to 0, we generate various forms of the model. For example, a model with constant deterministic and stochastic components is obtained by setting $r_1 = \sigma_1 = 0$.

The statistical interpretation of Equation (2) is that given $W(t) = w$, dW is normally distributed with mean $(r_0 + r_1 w)dt + o(dt)$ and variance $(\sigma_0 + \sigma_1 w)^2 dt + o(dt)$, where $o(dt)$ denotes higher powers of dt . We used techniques of Maximum Likelihood Estimation (MLE) to determine the most likely values of the parameters using the data shown in Figure 1(c) and Equation (2). We then used the Akaike Information Criterion (AIC) (Burnham & Anderson 2002) to select the most parsimonious models among the variants in which one or more of the parameters equal to zero, and to weight the support that the data give to the various models.

In the Appendix we show that the probability of success $u(w)$ satisfies

$$\frac{(\sigma_0 + \sigma_1 w)^2}{2} \frac{d^2 u}{dw^2} + (r_0 + r_1 w) \frac{du}{dw} = 0 \quad (3)$$

(also see Mangel & Ludwig 1977; Keizer 1987; Stratonovich 1992; Mangel 1994).

Since $u(w)$ is the probability of reaching w_u editors before falling back to 0 given that the current number of editors is w , the associated boundary conditions are $u(0) = 0$ and $u(w_u) = 1$. For the Wikipedia with data shown in Figure 1(c), the solution to Equation (3) is a prediction of the probability success given the data up to month 18.

To reflect model uncertainty, at each value of the number of editors, we computed the mean weighted by AIC weight (Burnham & Anderson 2002) and variance (across the models) of the probability of success. In order to account for parameter uncertainty within each model, rather than between models, we used Markov Chain Monte Carlo (MCMC) methods to obtain distributions for the parameters in each of the models. We used a Bayesian

approach to describe the joint posteriors of the model parameters and generate median, central 68% and central 95% credible intervals on $u(w)$. These details are described in the Appendix.

Based only on a single language Wikipedia, we cannot assess model performance in terms of how well predicted success probability matches the frequency of success of replicate wikis. To assess the ability of the AIC-determined best model to predict the relative risk faced by multiple Wikipedias, we downloaded data on monthly counts of ‘active users’ (at least five edits per month) in 268 different language Wikipedias.

For each language, we identified the first month with a non-zero editor count and then extracted the first 18 monthly counts, allowing the estimation of 18 values of the number of editors and 17 values of the monthly change in the number of editors. We then fit the best-supported and most parsimonious model according to our original analysis for the English Wikipedia to each dataset, assessed uncertainty of the parameters for each language, and estimated $u(w)$ its associated uncertainty for a range of values of w , including the actual editor count on the 18th month of existence of Wikipedia in that language. Since some languages have an inherently small user base and would be unlikely to sustain more than 1000 editors even if successful, we used both 50 editors and 1000 editors as the upper value w_u .

Results

In Table 1 we show the best models identified by the AIC analysis and in Table 2 the parameters for the five best models, which have 97% of the AIC weight. In Figure 2(a), we show the weighted mean probability of success with error bars determined by the square root of the variance. From this figure, we see that based on the weighted mean, once the Wikipedia crossed the 250-editor mark there was about a 70% chance of growing to 1000 editors before returning to 0 editors. The relatively wide error bars in Figure 2(a) are due to the considerable variation in the individual solutions, which we show in Figure 2(b).

Table 1. Results of the AIC analysis for the data shown in Figure 1(c) under different assumptions about the stochastic dynamics* (k = number of parameters).

Model	k	AICc	AIC Weight ($AIC_w(i)$)
1) $r = r_0, \sigma = \sigma_0$	2	232.01	0.36
2) $r = r_0, \sigma = \sigma_0 + \sigma_1 w$	3	232.22	0.32
3) $r = r_1 w, \sigma = \sigma_0$	2	234.12	0.12
4) $r = r_0 + r_1 w, \sigma = \sigma_0$	3	234.62	0.098
5) $r = r_0 + r_1 w, \sigma = \sigma_0 + \sigma_1 w$	4	235.57	0.061
6) $r = r_1 w, \sigma = \sigma_0 + \sigma_1 w$	3	238.73	0.012
7) $r = r_0, \sigma = \sigma_1 w$	2	239.00	0.011
8) $r = r_1 w, \sigma = \sigma_1 w$	2	240.95	0.004
9) $r = r_0 + r_1 w, \sigma = \sigma_1 w$	3	241.64	0.0029

*Given $W(t) = w$ and setting $dW = W(t + dt) - W(t)$; $dW \sim N((r_0 + r_1 w)dt + o(dt), (\sigma_0 + \sigma_1 w)^2 dt + o(dt))$; where $N(\mu, \sigma^2)$ is a normal distribution with mean μ and variance.

Table 2. Non-zero MLE values of parameters for the five best-supported models from Table 1.

Model	Parameters
1	$r_0 = 81.99, \sigma_0 = 192.86$
2	$r_0 = 78.79, \sigma_0 = 101.30, \sigma_1 = 0.13$
3	$r_I = 0.0453, \sigma_0 = 205.20$
4	$r_0 = 115.04, r_I = -0.0467, \sigma_0 = 190.74$
5	$r_0 = 66.70, r_I = 0.0361, \sigma_0 = 95.23, \sigma_1 = 0.14$

In Figure 3, we show two-dimensional plots of the joint posteriors of all pairs of parameters for the English language Wikipedia, but in the case of more complicated models these are still integrated over the uncertainty in the remaining, unseen parameters.

In Figure 4, languages of non-English Wikipedias with similar success probabilities predicted by Model 1 (individual results are in the online supplemental information) are grouped together and the actual fraction of success is counted for each group. In general, languages with a higher predicted probability of success were more often successful, but there was not a close correspondence between the predicted success probability and the fraction of languages succeeding. In particular, most of the data fall below the 1:1 line if we use the MLE success

probability (Figure 4a) but are on either side of the 1:1 line if we use the 68% credible interval (Harte 2001; Figure 4b). The failure of Model 1 to more accurately predict the probability of success across all the Wikipedias may indicate that each language needs its own best model; in the case of languages with small numbers of readers, nonlinear terms in Equation (1) may become important long before the 50-editor mark is reached.

Discussion

Simberloff (2009) recently reviewed the role of propagule pressure in biological invasions and our results have a clear analogue through the mean rate of growth and its dependence on the current number of editors. The success of a social collaboration network can also be viewed as an “epidemic”, characterized (Gladwell 2000) by contagion – the deterministic component Equation (1), which measures the mean rate of growth; and stickiness – the stochastic component of Equation (1), which measures the volatility of editor numbers. Individuals interested in increasing the success probability of a social collaboration network (e.g. Lewis et al. 2012) could use our methods to ask if the probability of success is improved more by increasing the deterministic component or by decreasing the volatility.

The probability that we compute does not characterize the sustainability (large-scale adoption in the sense of Mader (2008)) of a wiki or other social collaboration network, but does identify those that are more likely to succeed than not. Indeed, a wiki could fall to 0 editors and then rebound – the analogue of a local extinction and then re-invasion. Similarly, we have not discussed a mechanism by which the social collaboration network grows in its nonlinear phase. Mechanism becomes much more important if one wishes to understand the full trajectory, including the point of inflection, saturation and fluctuations around the level of saturation. Although that is a subject for a different paper, we can give a few comments here. First, since editors may join a wiki because of other editors (“my friend is doing this, so I will too”) or because of articles that inspire one to become an editor, a minimal model for mechanism should likely include articles and editors as states. In addition, we may also need to consider the behavioral ecology of editors and the “fitness” metric involvement in a social network. Second, although the paper is about social networks, we assumed no influence of structure on wiki success. That is, we used the simplifying assumption that all editors are the same (have the same influence in generating new editors). But structure is a key characteristic of networks, and social networks often have hubs, where few individuals connect a large proportion of other less connected individuals. As with invasion biology, in which all invaders are not equal, there are likely key highly connected editors that have more impact than others. We hypothesize that if editors are connected to their articles in a small-world network, then the predicted probability of success of the network would in general be less than the observed probability of success because most editors have little influence on the number

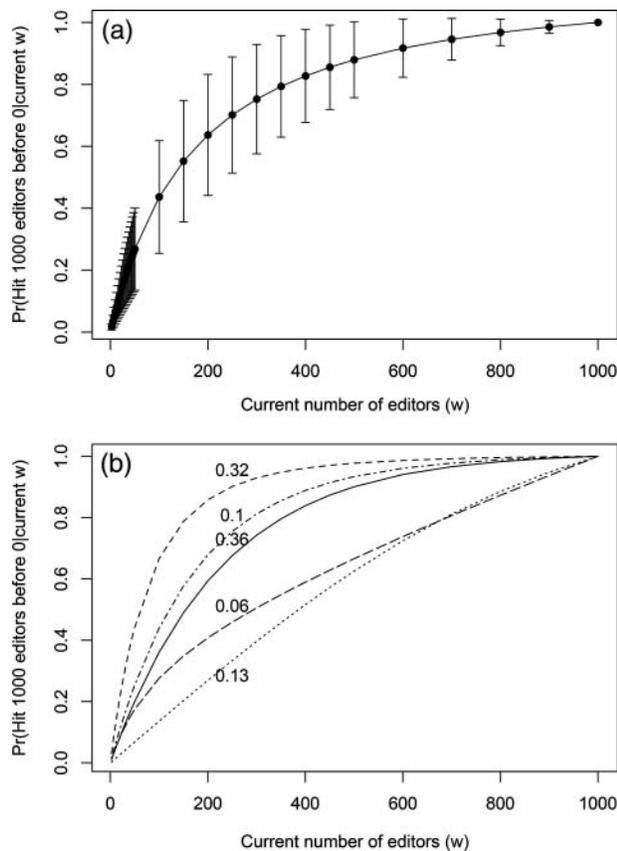


Figure 2. (a) The weighted mean probability of the English Wikipedia hitting 1000 editors before returning to 0 editors given the current number of editors, for the five top models in Table 1, with AIC weights rescaled to sum to 1. The error bars are determined by the square root of the AIC weighted variance (see Methods). (b) The individual solutions, along with their AIC weights.

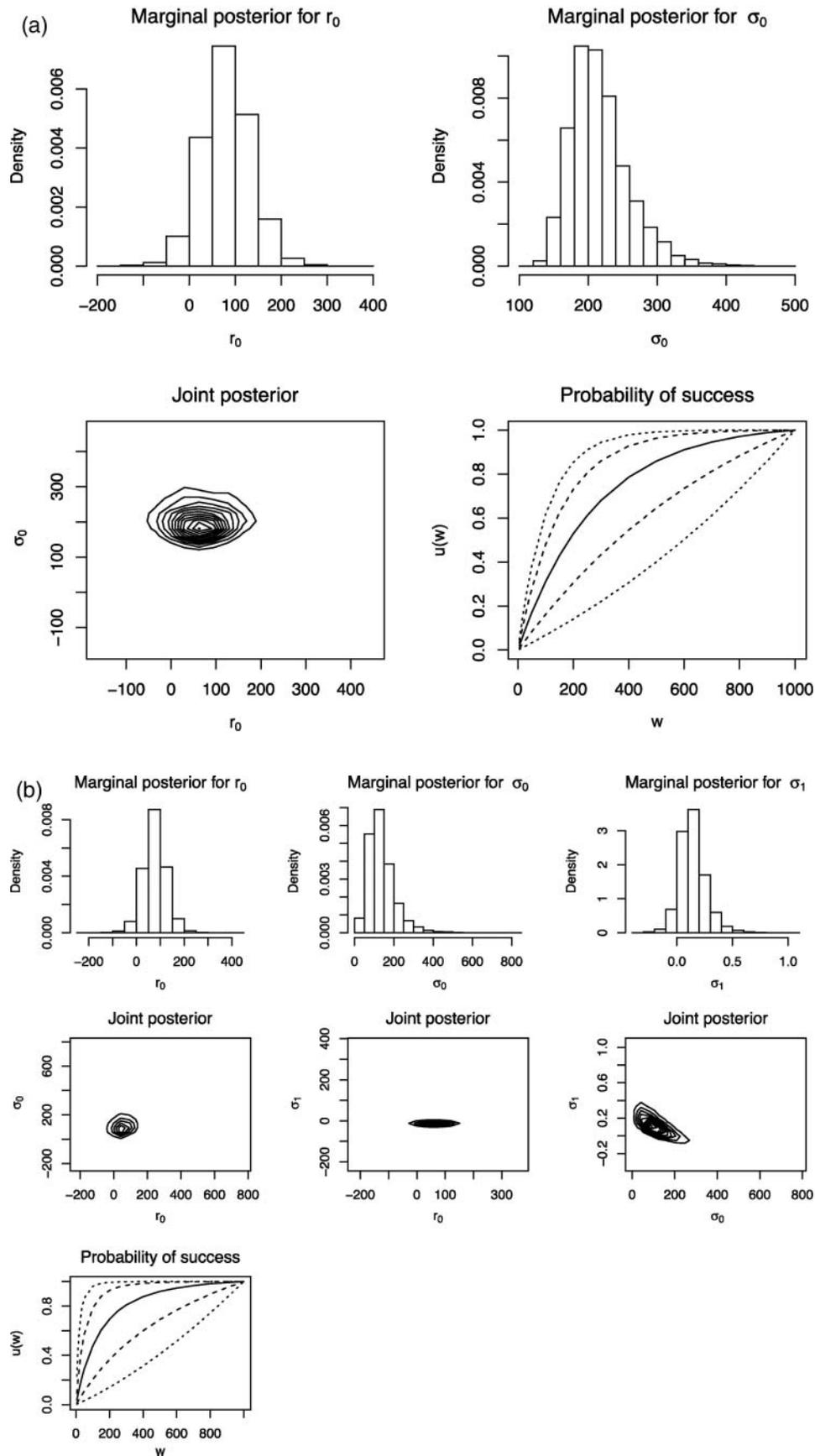


Figure 3. (a–e) Posterior distributions of parameters for the top five models for early dynamics of editors. For the plots of $u(w)$, the solid line is the posterior median, the heavily dashed lines are the 68% credible interval and the lightly dashed lines are the 95% credible interval. Panels a–e correspond to models 1–5.

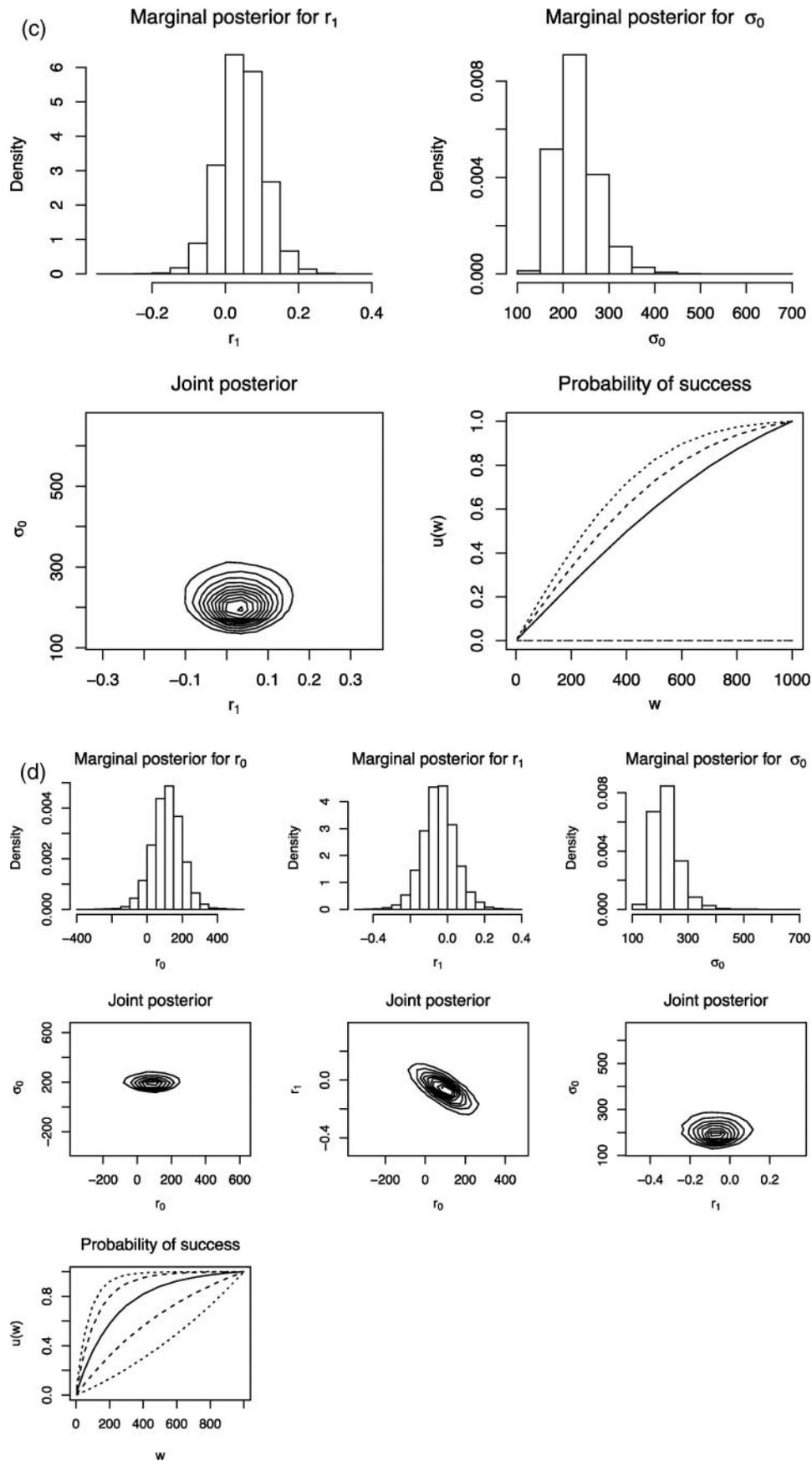


Figure 3. (a–e) Continued.

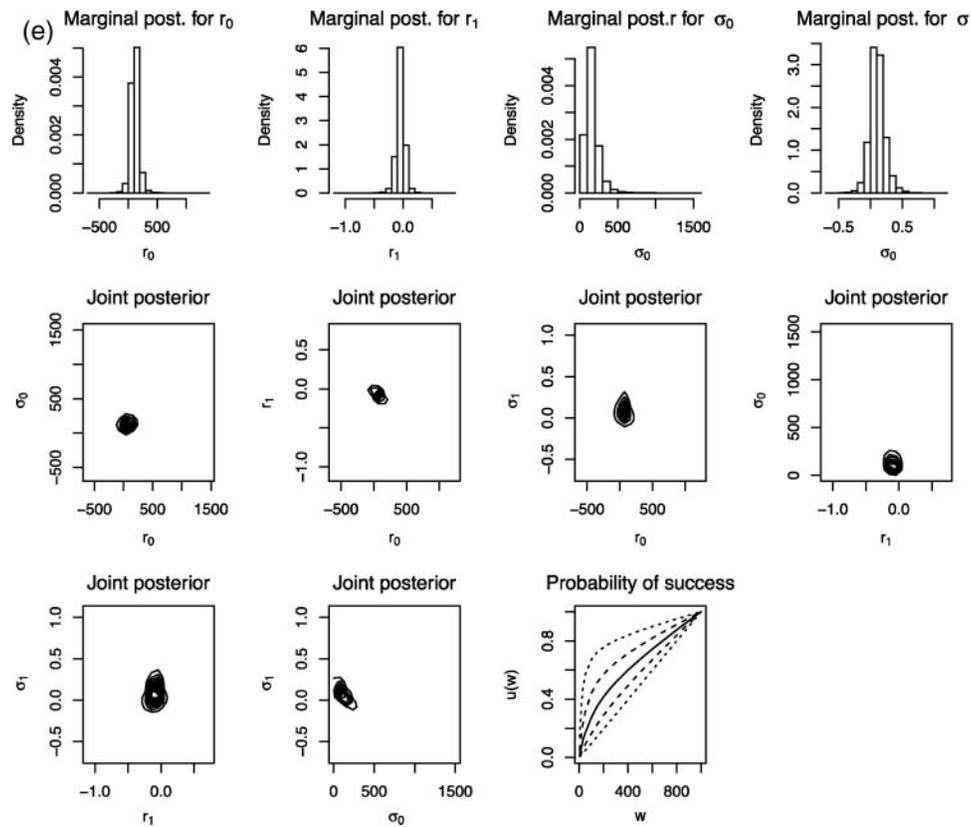


Figure 3. (a–e) Continued.

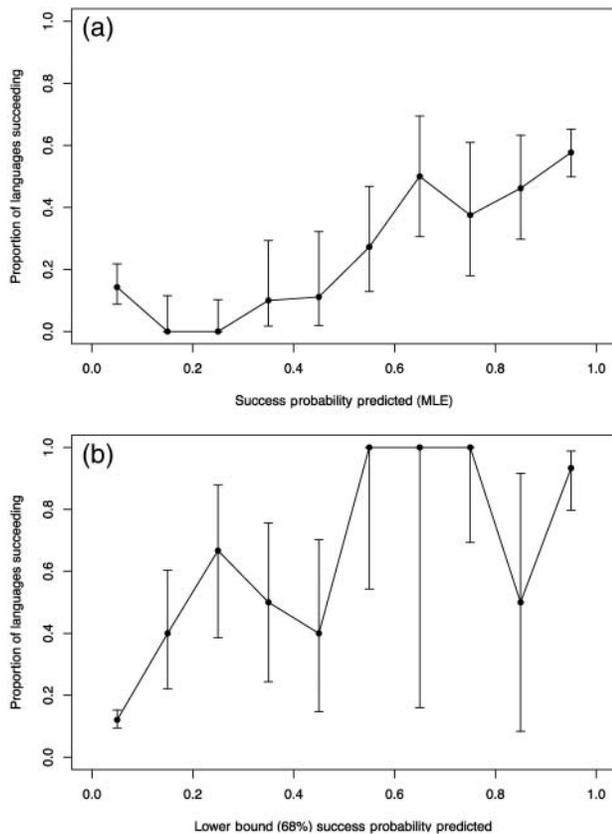


Figure 4. (a–b) Cross-language success in predicting the probability of different language Wikipedias succeeding. We bin languages: 1) by MLE predicted success, and plot the proportion of models with predicted success in each bin that actually succeeded (error bars are 68% binomial confidence intervals (9)); or 2) based on the lower bound of the 68% credible interval on success probability.

of articles, which could in part explain the results in Figure 4.

Our computation of the probability of success for different Wikipedias has additional analogies to the field of Population Viability Analysis (PVA) in conservation biology, which has the goal of predicting extinction probabilities for endangered populations (Gilpin & Soule 1986; Beissinger & Westphal 1998). While PVAs have proven useful in ranking relative risks and evaluating alternative management strategies (Brook et al. 2000), confidence intervals on extinction probability ranging nearly from 0 to 1 are common (Ludwig 1990; Satterthwaite et al. 2002) and results are better interpreted as rankings of relative risks rather than absolute predictions of outcome probabilities (Beissinger & Westphal 1998).

The first major step in making a network tool for collaboration in an organization is to conduct a pilot with both a time frame and a long-term vision (Mader 2008) – this is like seeding with a propagule. The methods we have described allow quantitative evaluation of the probability that the collaborative social network will succeed on a larger scale, given the data of the pilot. For that reason, our approach is broadly applicable and is an example of how ideas from population biology inform understanding of technology (Crawford 2001; Wischmann et al. 2012).

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Appendix. Further details on the methods

AIC analysis for the parameters

According to Equation (2), given $W(t) = w$,

$$dW \sim N((r_0 + r_1 w)dt + o(dt), (\sigma_0 + \sigma_1 w)^2 dt + o(dt)) \quad (4)$$

where $N(\mu, \sigma^2)$ is a normal distribution with mean μ and variance σ^2 , and $o(dt)$ denotes terms that are higher powers of dt .

We used maximum likelihood techniques, assuming the normal distribution for dW specified in Equation (4), to determine the most likely values of the parameters in Equation (2) using the data shown in Figure 1c. We report these in Table 1. We assessed support for each of the different models using AIC analysis.

Derivation and solution of the equation for the probability of success

From the definition of $u(w)$, the law of total probability (Mangel 2006) leads to

$$u(w) = E_{dW}\{u(w + dW)\} \quad (5)$$

Taylor-expanding the right-hand side of Equation (5) to second order gives

$$u(w) = E_{dW}\left\{u(w) + \frac{du}{dw}dW + \frac{1}{2}\frac{d^2u}{dw^2}dW^2 + o(dW^2)\right\} \quad (6)$$

In light of the properties of the increment of Brownian motion

$$\begin{aligned} E\{dW|W(t) = w\} &= (r_0 + r_1 w)dt + o(dt) \\ E\{dW^2|W(t) = w\} &= (\sigma_0 + \sigma_1 w)^2 dt + o(dt) \end{aligned} \quad (7)$$

so that Equation (6) becomes

$$u(w) = u(w) + (r_0 + r_1 w) \frac{du}{dw} dt + \frac{(\sigma_0 + \sigma_1 w)^2}{2} \frac{d^2u}{dw^2} dt + o(dt) \quad (8)$$

We divide by dt and let $dt \rightarrow 0$ to obtain

$$\frac{(\sigma_0 + \sigma_1 w)^2}{2} \frac{d^2u}{dw^2} + (r_0 + r_1 w) \frac{du}{dw} = 0 \quad (9)$$

In light of the definition of $u(w)$, the boundary conditions associated with Equation (9) are

$$u(0) = 0; u(w_u) = 1 \quad (10)$$

The general solution of Equation (9) is

$$u(w) = \frac{\int_0^w \exp \left[-2 \int_0^y \frac{r_0 + r_1 x}{(\sigma_0 + \sigma_1 x)^2} dx \right] dy}{\int_0^{w_u} \exp \left[-2 \int_0^y \frac{r_0 + r_1 x}{(\sigma_0 + \sigma_1 x)^2} dx \right] dy} \quad (11)$$

We evaluate this integral exactly for Model 1

$$u(w) = \frac{1 - e^{-\frac{2r_0 w}{\sigma_0^2}}}{1 - e^{-\frac{2r_0 w_u}{\sigma_0^2}}} \quad (12)$$

For cases in which the MLE $r_0 = 0$, Equation (12) must be evaluated using l'Hospital's rule (or equivalently by Taylor-expanding the exponentials as $r_0 \rightarrow 0$).

We evaluated the solution for Model 2

$$u(w) = \frac{\int_0^w \exp \left[\frac{1}{\sigma_1} \bullet \frac{2r_0}{\sigma_0 + \sigma_1 y} \right] dy}{\int_0^{w_u} \exp \left[\frac{1}{\sigma_1} \bullet \frac{2r_0}{\sigma_0 + \sigma_1 y} \right] dy} \quad (13)$$

using numerical integration.

The solution for Model 3

$$u(w) = \frac{\int_0^w \exp \left[-\frac{r_1}{\sigma_0^2} y^2 \right] dy}{\int_0^{w_u} \exp \left[-\frac{r_1}{\sigma_0^2} y^2 \right] dy} = \frac{\int_0^{\frac{w\sqrt{2r_1}}{\sigma_0}} \exp \left[-\frac{y^2}{2} \right] dy}{\int_0^{\frac{w_u\sqrt{2r_1}}{\sigma_0}} \exp \left[-\frac{y^2}{2} \right] dy} \quad (14)$$

can be evaluated quickly by using the numerical approximation for normal distributions (Abramowitz & Stegun 1964).

We also evaluated the solution for Model 4

$$u(w) = \frac{\int_0^w \exp \left[-\frac{2}{\sigma_0^2} (r_0 y + \frac{1}{2} r_1 y^2) \right] dy}{\int_0^{w_u} \exp \left[-\frac{2}{\sigma_0^2} (r_0 y + \frac{1}{2} r_1 y^2) \right] dy} \quad (15)$$

numerically.

Finally, for Model 5, no simplifications are possible for the integrands in the exponentials, so we used Equations 3.3.16–3.1.19 from Abramowitz and Stegun (1964) for evaluation of integrals of the form $\int \frac{mx+n}{ax^2+bx+c} dx$.

Construction of Figure 2(a)

To construct Figure 2(a), we let subscript i denote the result obtained from Equation (11) when model i in Table 1 is used (with weights rescaled to sum to 1.0 for the top five models) and define

$$\begin{aligned} \bar{u}(w) &= \sum_{i=1}^5 AIC_w(i) u_i(w) \\ \bar{u}^2(w) &= \sum_{i=1}^5 AIC_w(i) u_i^{2V}(w) \\ Var(u(w)) &= \bar{u}^2(w) - (\bar{u}(w))^2 \end{aligned} \quad (16)$$

to represent the AIC weighted solutions for a mean of Equation (11) and a measure of variability around that mean. For Figure 2(a), we show the weighted mean with error bars determined by $\sqrt{Var(u(w))}$.

Bayesian methods

Our goal is to estimate the joint posterior for the model parameters, which we denote by a vector v whose form will vary based on the model under consideration. The posterior predictive distribution for the success probability $u(w)$ can then be determined by applying the formula for $u(w)$ to draws of model parameters from their joint posterior distribution.

The maximum likelihood fits described earlier allow us to calculate the probability distribution of dW given the parameters and the current number of editors, which we denote by $p(dW|v, W)$. To generate the posterior for the model parameters we compute the probability distribution of the parameters, given the current number of editors and the observed change in editors, which we denote by $p(v|W, dW)$.

Using Bayes's theorem and assuming independent priors on W, dW and σ and assuming independent priors on del parameter $p_1(v|W, dW)$ given the current number of editors and the change in the number of editors is

$$p_1(v|W, dW) = \frac{p_0(v)p(dW|W, v)}{\int p_0(v)p(dW|W, v)dv} \propto p_0(v)p(dW|W, v) \quad (17)$$

In this expression, $p_0(v)$ is the prior probability for the parameters (we assume limited knowledge and thus uniform, unbounded priors except that $\sigma_0 > 0$ since the standard deviation in growth rate must be positive even as W becomes small) and $p(dW, W|v)$ is of the probability of drawing each observed value of dW from a normal distribution with mean and standard deviation calculated according to the current model formulation, given W and the proposed values of v . The denominator in the middle expression in Equation (17) is a normalization constant, so that the posterior density integrates to 1. The final expression follows from this.

We approximated the posterior distribution for v by using Metropolis algorithm Markov Chain Monte Carlo sampling of the equation for the posterior density given above (Gelman et al. 2004). We used custom R code (R Development Core Team) with symmetric, normal proposal distributions manually tuned to give acceptance probabilities of ~ 0.4 . Within each iteration of the chain, we updated each element of v one parameter at a time, conditioned on the current value of the other parameters. After (potentially) updating each element of v , we calculated $u(w)$ for a series of values of w ranging from 2.5 to 50 in increments of

2.5 and from 50 to 500 in increments of 25 (and then up to 1000 in increments of 100 for English). We recorded each of these estimates of $u(w)$ to generate chains of draws from the posterior predictive distribution.

The priors we used are improper (do not have finite integrals), but our data had a bounded range of support (and sufficient power for likelihoods to dominate priors), resulting in proper posteriors. We also ran the models with a Jeffreys prior (Gelman et al. 2004) for σ_0 , $p(\sigma_0) \sim 1/\sigma_0$ for all $\sigma_0 > 0$, with essentially identical results. Since the posterior distributions of individual variables integrate over the full uncertainty in the remaining parameters, their modes do not always coincide exactly with the maximum likelihood estimates.

After manual tuning of the proposal distributions, for each model formulation (i.e. Models 1–5) or dataset (we extended this analysis to multiple languages – see below) we ran an initial

burn-in of 20,000 iterations, starting from the MLE estimates of v . We then used the diagnostic method of Geweke (1992) as implemented in “gewke.diag” in R library “coda” (Plummer et al. 2010) to compare the mean of the first 10% of the retained chain to the last 50% of the chain. If $|z|$ -scores for all elements of v and all estimates of $u(w)$ were < 2 , we considered the chains to have converged and burn-in adequate. If not, we ran an additional 20,000 iterations until the last 20,000 iterations yielded passing diagnostics. Finally, we used the Raftery and Lewis (1995) approach implemented via the command “raftery.diag” in library “coda” to calculate the recommended post burn-in length of the posterior chain for each parameter or predictive output required to estimate the .025 quantile with accuracy of 0.005 with 95% probability. We rounded the required chain length up to the nearest 20,000 (if $\leq 100,000$ iterations required) or 250,000.