

# The Virtuous Circle of Wikipedia

## Recursive Measures of Quality and Expertise

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### ABSTRACT

In open collaboration, knowledge is created and iteratively improved by a multitude of editors, who freely choose what should be their contributions. Each knowledge unit (e.g. article, source code file) is deeply tied to the expertise and the number of its contributors. Conversely, the expertise of contributors is a function of knowledge units contributed to. We propose a *bi-partite network random walker* model, which measures how editor expertise influences the quality of articles, how contributions to articles influence editor expertise, and so on, recursively. We calibrate the model on 12 Wikipedia categories, and find how the complex structure of knowledge production influences article quality and editor expertise. While the wisdom of crowds is better pulled in some categories, multiple editors create marginal dis-value in others. These differences can be explained from the ability of communities to organize, as well as from the very nature of knowledge created.

### Author Keywords

**open collaboration, bi-partite networks, contribution performance**

### INTRODUCTION

In online open collaboration, units of knowledge such as open source code files, Wikipedia articles, 3D-printing designs, are usually produced and improved collectively by a multitude of contributors. Some people devote numerous hours of labor improving existing content and adding new features, while most contributors only make minor changes. Yet, in addition to the power of the few, a mass of small changes can make the difference as a form of emergent collective intelligence [17]. This new form of labor organization, underlying open collaboration, is called peer-production, and heavily relies on Internet communication systems to be effective [1]. As the

Internet has become pervasive in modern societies, open collaboration has permeated to a broad variety of social contexts and industries [2].

Nonetheless, in the absence of formal rules that organize open collaboration, it has remained nearly impossible to account for individual contributions in the production of high quality and often reliable knowledge, as demonstrated for instance for Wikipedia [9]. Indeed, the most basic component of peer-production is *task self-selection*: participants in open collaboration freely choose how and when to contribute, with none or very limited vertical organization [1].

To add to the complexity of self-organized open collaboration projects, many communities exhibit critical cascades of iterative improvements, which in turn lead to super-linear productive bursts of contributions [23]. These highly non-linear, transient and intrinsically unpredictable bursts of iterative improvements are the hallmark of successfully organized communities. To enable productive bursts, a number of conditions must be met, which include transparency, self-censored clans, emergent technology, problem front-loading, distributed screening, and modularity [26]. Unfortunately, the dynamics of contributions are deeply entangled, and the ways individual inputs affect the value of collectively produced knowledge has remained largely obscure.

In this paper, we recognize that the value of each knowledge unit (e.g. article, source code file) is deeply tied to the expertise and the number of its contributors. Conversely, the expertise of contributors is a function of knowledge units contributed to. We therefore examine open collaboration projects, and their evolution, as a simple network that relates knowledge units and contributors. We propose a *bi-partite network random walker* model, which measures how editor expertise influences the quality of articles, how contributions to articles influence editor expertise, and so on, recursively. We calibrate the model on 12 Wikipedia categories of articles, and we show how the structure of contribution to knowledge can be disentangled, and how this structure, genuine to categories, influences the quality of knowledge produced and the expertise of editors.

The paper is organized as follows. The reader is first introduced to relevant literature. The method, data employed

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and the results are then presented and discussed. We finally present future research directions and conclude.

## RELATED WORK

To the best of our knowledge, our paper is the first attempt to quantify the value of collective contribution environments from the collaboration structure alone. Our model of bi-partite random walkers follows in the lineage of bi-partite networks – networks with two node types – in the global economy of countries competing for exporting products [13, 12]. The proposed recursive *method of reflections* helps understand the competitive advantage (i.e. *fitness*) of countries from the types of products they sell, and moreover, whether other countries export similar (i.e. *ubiquitous*) products. The key insight is that most competitive countries are found to not only export non-ubiquitous products, for which they can charge higher price, but also ubiquitous ones. The model of reflections has been improved and complemented in more recent work, mainly to improve its robustness [24, 7, 25, 6]. Caldarelli et al. [5] have proposed an alternative method, based on biased stochastic Markov chains, which helps further understand the mutual influence between nodes in bi-partite networks.

Apart from networks of economic competition, collaboration networks have been studied early on in network sciences, in particular for networks of co-authorship in scientific publications [19], as well as patterns of self-organization in bi-partite networks of actors-movies [21]. Similarly, the analysis of patterns in Wikipedia bi-partite networks confirmed the existence of overlapping cliques of densely connected articles and editors [14]. In the same study, clustering of densely connected cliques into larger modules [10] showed that editors clustered by interest with higher coordinated efforts in densely populated clusters [14].

Recent results show that the contribution dynamics of successful open source projects, stem from critical cascades of iterative improvements (commits), which in turn lead to super-linear *productive bursts* of contributions [23]. The conditions of emergence of productive bursts, include transparency, self-censored clans, emergent technology, problem front-loading, distributed screening, and modularity [26].

However, most empirical results in research on open collaboration was unable to uncover the mechanisms of value creation and performance, mainly because of the *bottom-up* emerging properties of peer-production [1]. The only notable result in this field was found during a series of Matlab contests aimed at collectively solving NP-hard problems. It was found that work shared as a public good helps individuals quickly reuse existing results, and thus, find better algorithms [11]. Source code submissions by individuals programmers were tested and benchmarked for their capacity to solve the assigned problem quickly, by executing the compiled code on a computer. Unfortunately, this approach is exclusively feasible for machine executable knowledge (i.e. software code) and in highly controlled environments. For Wikipedia, metrics such as edit or byte counts are widely used [4]. To overcome the roughness of these metrics, recent efforts have been

undertaken to develop stronger measures, to assess the expertise of contributors [8], as well as the quality of articles [27]. Nevertheless, these metrics provide limited insights on how editor expertise and article quality are creation collective contributions.

## METHOD

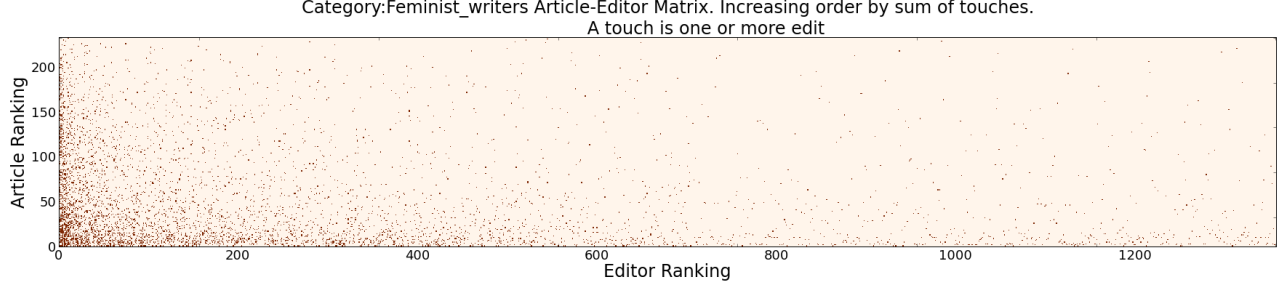
Measuring the structure of value creation by individuals is nearly impossible in most in open collaboration projects. In particular, when projects do not involve writing software code, they can hardly be compiled, executed and tested on computers. As exemplified in Wikipedia, the most common way to code knowledge is natural language (e.g. Chinese, English, Spanish, French, German), which can hardly be systematically tested for performance. Natural language is indeed the realm of subjective interpretation by humans.

Here, we present a method to model value creation and performance in such environments. This method neither relies on the content or on subjective metrics, such as the number of edits, nor on the number of bytes changed overall or per edit. We recognize that value can be brought by each editor, regardless of the frequency, or the length of her contributions. Only the number and the expertise of editors bring value to an article. And the expertise of editors can be measured from the number and the quality of articles they have modified at least once.

For that, we consider a simple input, which is a representation of the bi-partite network of editors and their contributions to articles. Namely, let us consider a matrix  $M_{ea}$  of all editors having contributed to a Wikipedia category of articles.  $M_{ea}$  takes value 1 if editor  $e$  has edited article  $a$ , and 0 otherwise. Note that  $M_{ea}$  only shows which editors have ever touched an article. We convert to a binary categorical input for this matrix because of the precedent set in ?? ?? ??, which each seek to move beyond the importance of edit count, claiming it to be spurious data when imagining the graph of editors, or measuring editor experience. For the category *Feminist Writers*, as presented on Figure 1,  $M_{ea}$  exhibits a triangular structure in which editors (resp. articles) are sorted (max on the bottom-left corner) by the number of articles they have touched (resp. by the number of editors who have touched each article).  $M_{ea}$  is the only input of the *bi-partite random walker* model described thereafter, for recursively characterizing the structure and the value of contributions in open collaboration, through the evaluation of editor expertise and article quality.

Given  $M_{ea}$ , the simplest way to assess the contribution value, the *expertise*, of an editor is obtained by summing the number of articles ever edited out of a set of articles. Similarly, a simple *quality* measure for an article is the sum of editors who have ever modified it, following the famous adage on open source development: “Given enough eyeballs, all bugs are shallow” [22]. These crude expertise and quality metrics for editors and articles, respectively given by,

$$\begin{cases} u_e^{(0)} = \sum_{a=1}^{N_a} M_{ea} \equiv k_e \\ u_a^{(0)} = \sum_{e=1}^{N_e} M_{ea} \equiv k_a \end{cases} \quad (1)$$



**Figure 1.** Typical  $M_{ea}$  matrix for a Wikipedia category (here, *Feminist Writers*) ordered on both dimensions by descending order of number of articles modified by an editor (horizontal axis) and of number editors who have modified an article (vertical axis). The structure of  $M_{ea}$  is triangular and shows that some editors have a pervasive activity over articles, while most editors edit only a few. Similarly, some articles receive widespread attention by editors, while most articles are modified only by a few editors.

are the zero<sup>th</sup> order of our algorithm. They are the initial step of the *method of reflections* proposed by Hidalgo et al. [13, 12], which derives the value of producing entities (i.e. editors) from products (i.e. articles), and *vice versa*. To help capture the intuition behind the method of reflections for open collaboration, we walk through the first and second iterations, as they are adapted to our study of Wikipedia:

- **1<sup>st</sup> order iteration,**

- **Articles:** If an article has been edited by higher expertise editors, it is of higher quality. That is, quality is a function of expertise calculated from zero<sup>th</sup> iteration expertise scores.

- **Editors:** Conversely, if an editor has contributed to higher quality articles, her expertise is higher. That is, expertise is a function of quality calculated from zero<sup>th</sup> iteration quality scores.

- **2<sup>nd</sup> order iteration,**

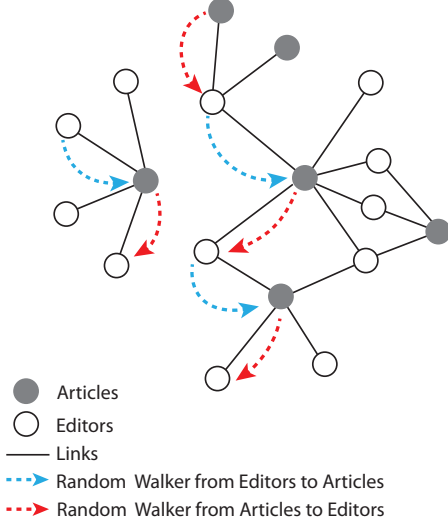
- **Articles:** If an article has been changed by higher expertise editors who have edited higher value articles, which in turn have been edited by higher expertise contributors, the article quality is higher. That is, quality is a function of expertise calculated from 1<sup>st</sup> iteration expertise scores.
- **Editors:** Conversely, if an editor has edited higher quality articles, which have been edited by better editors who have edited higher quality articles, then expertise is higher. That is, expertise is a function of quality calculated from 1<sup>st</sup> iteration quality scores.

- **And so on, recursively.**

Although interpretation is difficult past the very first iteration steps, at each iteration, the algorithm incorporates additional information on the quality of the articles and expertise of editor from the neighboring nodes in the bi-partite network. The higher order iterations of the method of reflections are written as,

$$\begin{cases} u_e^{(n+1)} = \frac{1}{k_e} \sum_{a=1}^{N_a} M_{ea} u_a^n \\ u_a^{(n+1)} = \frac{1}{k_a} \sum_{e=1}^{N_e} M_{ea} u_e^n \end{cases} \quad (2)$$

The method of reflections however suffers from a problem, which is rooted in the equal weights given to article and editor scores obtained at the previous iteration. As a result, the method converges to a fixed point with all editors (resp. all articles) having the same value, as a case of consensus dynamics [5]. It has therefore been proposed to consider giving variable weights to the scores from the previous iteration as a Markov process of random walkers on a bi-partite network, jumping with some probability from one node type to another node type [5]. A schematic representation of the random walk process on a bi-partite network is depicted in Figure 2. The intuition is the following: a random walker jumps with some probability from an editor to a given article (i.e. the editor’s expertise is positively influenced by the article’s quality), and



**Figure 2.** Representation of random walkers jumping from editors to articles (red dotted arrows) and from articles to editors (blue dotted arrows). The intuition is the following: a random walker jumps with some probability from an editor to a given article (i.e. the editor’s expertise is positively influenced by the article’s quality), and with another probability from an article to a given editor (i.e. the value of the article positively influences the editor’s expertise).

with another probability from an article to a given editor (i.e. the value of the article is positively by the editor’s expertise). The matrix  $M_{ea}$  determines whether a jump between each pair of nodes is possible. If two nodes  $e$  and  $a$  are not directly connected  $M_{ea} = 0$ , and the transition probability is 0. Conceptually, the *bi-partite network random walker* model is an extension of the single node type (i.e. Web pages) *Page Rank* Google search algorithm [20] to two kind of nodes.

According to Caldarelli et al. [5], we reformulate the method of reflections to account for jumps of the random walker on the bi-partite network of editors and articles. We call  $w_e^{(n)}$  the expertise of an editor and  $w_a^{(n)}$  the quality of an article at the  $n^{th}$  iteration. We define the following Markov process on the bi-partite network of collaboration,

$$\begin{cases} w_e^{(n+1)}(\alpha, \beta) = \sum_{a=1}^{N_a} G_{ea}(\beta) w_a^{(n)}(\alpha, \beta) \\ w_a^{(n+1)}(\alpha, \beta) = \sum_{e=1}^{N_e} G_{ae}(\alpha) w_e^{(n)}(\alpha, \beta) \end{cases} \quad (3)$$

with  $G_{ea}$  the probability to jump from article  $a$  to editor  $e$  in a single step, and the probability  $G_{ae}$  to jump from editor  $e$  to article  $a$  also in a single step. These transition probabilities are given by,

$$\begin{cases} G_{ea}(\beta) = \frac{M_{ea} k_e^{-\beta}}{\sum_{e'=1}^{N_e} M_{e'a} k_{e'}^{-\beta}} \\ G_{ae}(\alpha) = \frac{M_{ea} k_a^{-\alpha}}{\sum_{a'=1}^{N_a} M_{ea'} k_{a'}^{-\alpha}} \end{cases} \quad (4)$$

The transition matrices  $G_{ea}(\beta)$  and  $G_{ae}(\alpha)$  depend only on

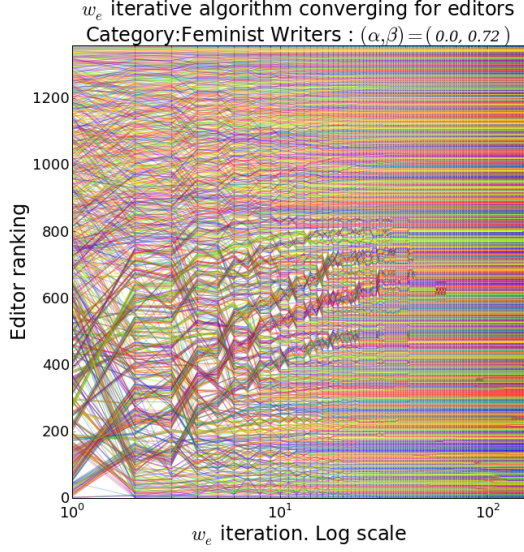
the initial conditions: the binary matrix  $M_{ea}$ , as well as  $k_e$  and  $k_a$  given by (1). The variables  $\alpha$  and  $\beta$  control the transition probabilities in a similar way. We shall therefore explain only how  $\beta$  influences the probability to jump from an article to an editor (i.e. the value of the article positively influences the editor’s expertise). For  $\beta = 0$ , we recover the zero<sup>th</sup> order iteration (1). For  $\beta > 0$ , the probability to jump from article  $a$  to editor  $e$  is a power law function  $\sim 1/k_e^\beta$  of the sum of articles  $k_e$  modified by editor  $e$ . Hence, the larger  $k_e$ , the lower the probability to jump from  $a$  to  $e$  relative to other editors. On the contrary, if  $\beta < 0$  the probability to jump from an article to an editor is a positive function of the sum of articles modified by the editor. For  $-1 < \beta < 0$ , the function is concave, while for  $\beta < -1$ , the function is convex, which means that the more articles have been edited by the editor, the even more the positive influence on articles. In a nutshell,  $\beta$  relates the amount of articles edited on the overall editor’s expertise, which in turn has an influence on each edited article (along with the influence of other editors). If  $\beta \gg 0$ , the positive influence of the number of contributed articles on the editor’s expertise decreases. If  $\beta$  close to 0, the number of contributed articles increases linearly the editor’s expertise. The same considerations hold for  $\alpha$  and the probability  $G_{ae}(\alpha)$  to jump from an editor to an article (i.e. the expertise of the editor positively influences the quality of an article).

After each iteration, we have expertise and quality scores, which allow for the ranking of editors and articles respectively. When the rankings for both editors and articles do not change in two successive iterations we consider that the *bi-partite network random walker* model has converged. We have verified that the method converges on all our 12 Wikipedia categories. Figure 3 shows the evolution of expertise  $w_e$  ranked among editors having contributed to articles in the *Feminist Writers* category on Wikipedia for the set of control parameters  $(\alpha, \beta) = (0, 0.72)$ . Starting from the sum of contributed articles as the initial step, we can see how the algorithm progressively ranks editors: some editors with initial low rank (i.e. with few articles edited), get a higher rank as the number of iterations increases. They most probably have edited and contributed to few, but high quality articles. Similarly, some initially high ranked editors, gradually drop in the ranking. They have edited many, but low quality articles. In the case of category *Feminist Writers*, the algorithm converges after 64 iterations.

The parameters  $\alpha$  and  $\beta$  control how editors and articles influence each other at the level of the whole bi-partite collaboration network. Upon calibration with ground-truth editor expertise and article quality metrics, these control parameters thus directly inform on the structure of peer-production, and how contributions benefit the whole open collaboration project.

## DATA

We seek to find values of  $\alpha$  and  $\beta$  that minimize the distance between rankings given by the bi-partite network random walker model, which takes the matrix  $M$  as unique input, and ground-truth metrics on editor expertise and article



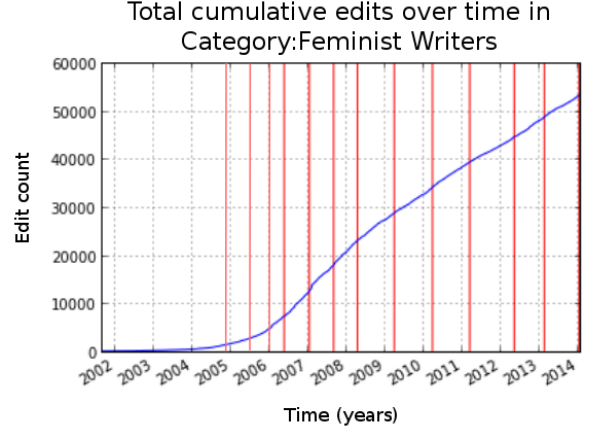
**Figure 3.** Convergence of the ranked expertise  $w_e$  of editors having contributed to articles in the Feminist Writers category on Wikipedia for arbitrary control parameters:  $(\alpha, \beta) = (0, 0.72)$ . Starting from the sum of contributed articles as the initial step, we can see how the algorithm progressively ranks editors: some editors with initial lowest rank, i.e. with few articles edited, get a higher rank as the number of iterations increases. Similarly, some initially high ranked editors, gradually drop in the ranking. In the case Wikipedia categories, the algorithm converges with clearly stable ranks, after 64 iterations.

quality, obtained independently from Wikipedia. We perform the model calibration for 13 snapshots (see Figure 4) for each of the 12 categories of Wikipedia articles presented in Table 1. For each category and snapshot, we build the binary matrix  $M$  by parsing all edit histories of all articles up to the snapshot time. We set  $M_{ea} = 1$  for editor  $e$  having modified article  $a$ , and  $M_{ea} = 0$  otherwise. In order to eliminate page vandals, we considered only editors who made 5 or more edits to any article in the category. We also discarded all software robots (i.e. *bots*) that programmatically edit Wikipedia.

To calibrate  $\alpha$  and  $\beta$ , we resorted to state-of-the-art ground-truth evaluations for editor expertise  $\bar{w}_e$  and article quality  $\bar{w}_a$ . From these exogenous evaluations, we ranked editors

| Category                    | Articles | Editors | Edits   |
|-----------------------------|----------|---------|---------|
| American male novelists     | 2,460    | 9,946   | 224,783 |
| 2013 films                  | 1,896    | 5,215   | 150,956 |
| American women novelists    | 1,936    | 5,968   | 138,716 |
| Nobel Peace Prize laureates | 104      | 4,165   | 91,522  |
| Sexual acts                 | 93       | 2,190   | 45,901  |
| Economic theories           | 212      | 1,145   | 28,658  |
| Feminist writers            | 233      | 1,357   | 25,738  |
| Yoga                        | 123      | 730     | 25,315  |
| Military history of the US  | 180      | 854     | 20,172  |
| Counterculture festivals    | 66       | 578     | 10,515  |
| Computability theory        | 92       | 272     | 7,117   |
| Bicycle parts               | 70       | 210     | 4,981   |

**Table 1.** Size statistics of investigated Wikipedia categories sorted by total edits.



**Figure 4.** Cumulative edits made in Category *Feminist writers* (blue line). Vertical red lines represent the 13 snapshots taken at 2.5%, 5%, 7.5% and then, 10%, 20%, 30%, ..., 100% of edits.

and articles according to their expertise and quality respectively. We then performed a grid search for values of  $\alpha^*$  and  $\beta^*$ , which maximize the Spearman rank-correlation  $\rho_e$  and  $\rho_a$  between rankings obtained from the bi-partite random walker model ( $w_e, w_a$ ) and from exogenous metrics ( $\bar{w}_e, \bar{w}_a$ ). Actually,  $(\alpha^*, \beta^*)$  must maximize both  $\rho_e$  and  $\rho_a$ , even though  $\rho_e$  and  $\rho_a$  might actually be different. The optimization function of  $(\alpha^*, \beta^*)$  is given by,

$$\begin{cases} (\alpha^*, \beta^*) = \operatorname{argmax}_{\alpha, \beta} (\rho_e) \\ (\alpha^*, \beta^*) = \operatorname{argmax}_{\alpha, \beta} (\rho_a). \end{cases} \quad (5)$$

The set  $(\alpha^*, \beta^*)$  characterizes how value flows from editors to articles, and from articles to editors, in the bi-partite network of collaboration in Wikipedia.

The ground-truth metrics used are taken from computer supported collaborative work literature. In trying to classify editor experience we acknowledge the proposal by Geiger and Halfaker [8], to move past edit count and use "labor hours". This accounts for the well decried fact that all edits are not equal, and rather counts the temporal length and editor has spend editing. It is calculated for each editor by taking contribution history up to the snapshot point. All edits made within 1 hour of a previous edit are counted in an *edit session*. If more than one hour separates two edits, a new period of edits starts. The expertise expressed in labor hours is the sum of edit sessions. For the calculation of ground-truth expertise, we only consider edits for a given category, although the same editor might have edited other categories of articles in Wikipedia. Our measure of actual article quality is performed through a combination of 5 text analysis metrics: (i) ratio of mark-up to readable text, (ii) number of headings, (iii) article length, (iv) citations per article length, (v) outgoing intra-Wiki links. These metrics are used to determine quality on Wikipedia [27] [18], and have been used in the CSCW literature in different combinations [16] [3]. We performed principal component analysis (PCA) for each category and snapshot in order to reduce dimensionality from 5 metrics to a single



one (i.e. the principal component). The variance explained by the principal component varied between 0.5 and 0.72, confirming the dominance of the axis of maximum variance.

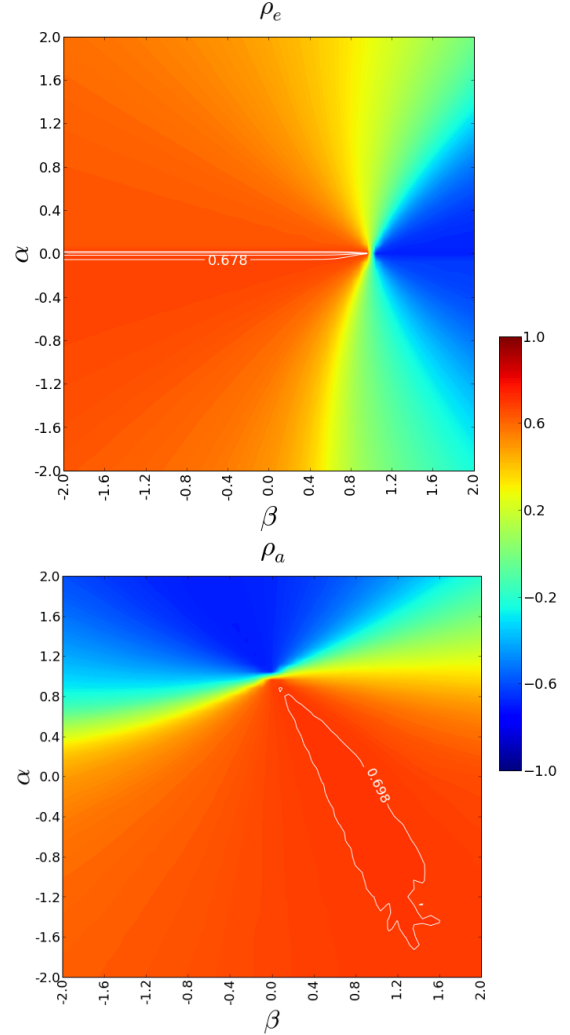
A further point should be made about whether our exogenous expertise and quality measures are independent. Earlier on links between expert editors and quality articles were claimed [?], and would seem intuitive. Yet, subsequently, there have been claims against such universal links which point out that key social interactions are not accounted for with these measures [15]. Intuitively this link rests on the collaborativeness of the articles and editors in question. With collaboration expertise will translate into article quality. However, given antagonistic, warring editors expertise will not improve article quality.

## RESULTS

To understand how contribution value *flows* from editors to articles, and from articles to editors, we calibrated the control parameters ( $\alpha^*, \beta^*$ ) of the bi-partite network random walker model on 12 Wikipedia categories (c.f. Table 1) with 13 snapshots each (Figure 4). Figure 5 shows typical optimization landscapes, which maximize the rank correlation  $\rho_e$  (upper panel) between editor expertise  $w_e$  obtained from the model and expertise obtained from state-of-the-art measures  $\bar{w}_e$ . The same is done for rank correlation  $\rho_a$  between  $w_a$  and  $\bar{w}_a$  (lower panel).

The maximum achievable rank-correlation with ground-truth expertise and quality metrics for respectively editors [8] and articles [27] shows that the bi-partite network random walker model accounts particularly well for both quality of articles ( $0.58 < \rho_a < 0.91$ ) and expertise of editors ( $0.46 < \rho_e < 0.75$ ) at the last snapshot. Actually, the model reproduces very well, and very early the ranking of editors and articles according to the ground-truth metrics as shown on Figure 6. In particular, the quality of articles is very well accounted for, while the level of correlation with the ground-truth of editor expertise exhibits a slightly concave, or at least linear, increase.

For the latest snapshot (i.e. the state contributions in February 2014), we find that the best possible  $\alpha^*$  is 0 in all circumstances, while  $\beta^*$  varies considerably across categories. Table 2 shows the categories ordered by the optimal  $\beta^*$  (and  $\alpha^* = 0$  for the sake of clarity), as well as the corresponding maximum rank correlations  $\rho_e$  and  $\rho_a$ . Since there is no single optimal value for  $(\alpha^*, \beta^*)$ , but rather a space of optimal values for  $\rho_e$  and  $\rho_a$  separately, we have searched for a set of values that jointly maximizes both  $\rho_e$  and  $\rho_a$ . The optimal parameter  $\alpha^* = 0$  means that editor expertise always benefits from contributions as a linear function of the number of articles edited [compounded over iterations of the recursive algorithm defined by formula (3)]. However,  $\beta^*$  exhibits a continuum of values between 0 (*Bicycle parts* and *US Military History*) and 1.52 (*Sexual Acts*).  $\beta$  controls the influence of the number of editors on the quality of a given article. When  $\beta \approx 0$ , the quality of articles increases as a linear function of the number of editors who have modified them. For  $\beta \gg 0$ , the marginal gain of having more editors for a given article decreases. So, in that case, when the number



**Figure 5. Typical landscape of maximum correlation as a function of  $\alpha$  and  $\beta$  for articles (upper panel) and editors (lower panel). The contour line shows the 95<sup>th</sup> percentile of the rank correlation over the landscape. The category displayed here is *Feminist Writers*, for the last snapshot ending February 2014.**

of editors touching an article increases, the marginal quality improvement decreases.

$\beta^*$  is found to be generally stable over snapshots for categories, past the first 10% of overall contributions (i.e. the 4<sup>th</sup> snapshot). The stability of  $(\alpha^*, \beta^*)$  confirm that the control parameters of the bi-partite network random walker model describe a robust feature of the structure of value creation in the bi-partite network of editors contributing to articles. This additional result is also a first step towards robust predictions of editor expertise and article quality rankings, given successive inputs to new articles made by editors.

## DISCUSSION

Building on the method of reflections previously used for global economic networks of production, we have applied and tested the *bi-partite network random walker* model in

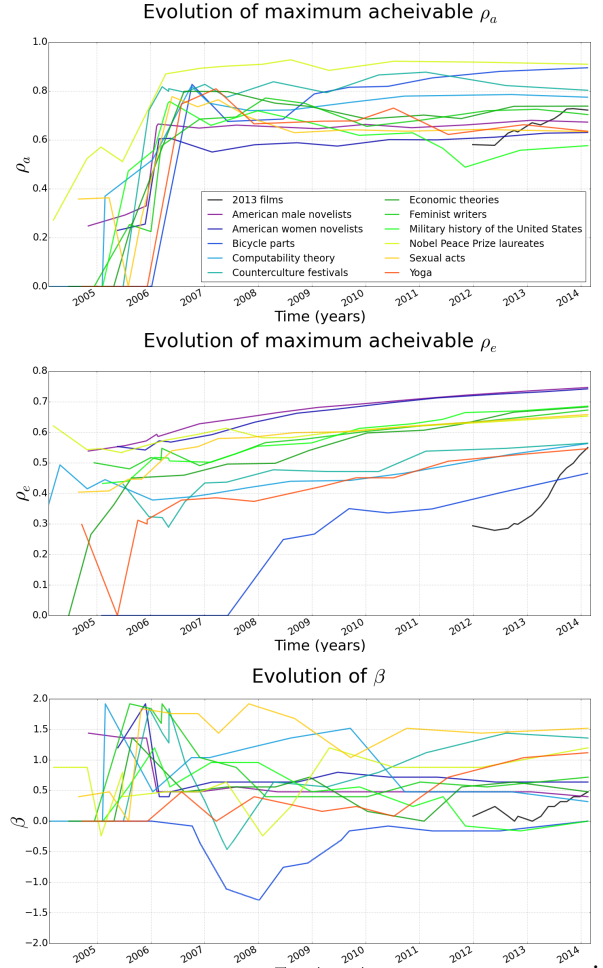
|    | Category                    | $\rho_a$ | $\rho_e$ | $\alpha$ | $\beta$ |
|----|-----------------------------|----------|----------|----------|---------|
| 1  | Bicycle parts               | 0.90     | 0.46     | 0.00     | 0.00    |
| 2  | Military history of the US  | 0.58     | 0.70     | 0.00     | 0.00    |
| 3  | Computability theory        | 0.77     | 0.56     | 0.00     | 0.32    |
| 4  | American male novelists     | 0.67     | 0.75     | 0.00     | 0.40    |
| 5  | 2013 films                  | 0.72     | 0.55     | 0.00     | 0.48    |
| 6  | Economic theories           | 0.74     | 0.70     | 0.00     | 0.48    |
| 7  | American women novelists    | 0.63     | 0.75     | 0.00     | 0.64    |
| 8  | Feminist writers            | 0.70     | 0.69     | 0.00     | 0.72    |
| 9  | Yoga                        | 0.64     | 0.57     | 0.00     | 1.12    |
| 10 | Nobel Peace Prize laureates | 0.91     | 0.66     | 0.00     | 1.20    |
| 11 | Counterculture festivals    | 0.80     | 0.61     | 0.00     | 1.36    |
| 12 | Sexual acts                 | 0.63     | 0.66     | 0.00     | 1.52    |

**Table 2.** Categories ordered by increasing  $\beta$  obtained from best rank-correlation  $\rho_a$  and  $\rho_e$  of the bi-partite network random walker with the ground truth. As shown on the upper panel of Figure 5, highest rank-correlation is always obtained for  $\alpha = 0$  suggesting that editors are experts in direct proportion to the number of articles they edit. The different values of  $\beta$  show the effect of marginal editors on a article. As  $\beta$  grows larger having more editors shows diminishing returns on article quality - "too many cooks spoil the broth".

the context of Wikipedia open collaboration. Our results show that the model accounts well for the quality of articles  $\langle \rho_a \rangle \approx 0.64$  and for the expertise of contributors  $\langle \rho_e \rangle \approx 0.72$ . Moreover, the evolution of  $\rho_e$  and  $\rho_a$  of categories under editing, exhibit strong stability. In particular, the adequacy of article ranking is very high early on, and thereafter stationary, suggesting that the model can quickly capture the quality of articles. For editor expertise, the adequacy increases steadily as categories get further developed.

This difference might be due to the roughness of the actual metrics for editors  $\bar{w}_e$ , expressed in labor-hours, compared to the quality of  $\bar{w}_a$ , which is an aggregate measure of five precise quality metrics. Nevertheless, the correlation of editor ranking with  $\bar{w}_e$  increases:  $\rho_e$  exhibits a convex increase over time, suggesting that it takes time (i.e. lots of articles edited) to capture well the expertise of editors. This is striking because the method is reflexive and the same information is incorporated on both dimensions from the input matrix  $M$ . While it will require further investigation to explain, we interpret this result in the following way: from Figure 1 and from Table 1, we see that there are always significantly more editors than articles for each category. This means that the probability for an article to get contributions early on is higher than the probability to find editors who have contributed to a lot of articles early. In other words, it takes more time to correctly rank editors because there are more editors compared to the number of articles in a given category.

We have also found  $\alpha \approx 0$  for all categories. This result shares similarity with [3], who found that "editor experience and the features of articles in their contribution history have a stronger influence on self-organization than article features and the attributes of their editors". In this way if editor expertise is more important, it makes sense that we find it,  $\alpha$ , to be a near-constant (although that doesn't explain why it should be zero). Allowing for a moment,  $\alpha = 0$  we can simplify our analytic solutions to gain a more intuitive interpretation of the calibration results.



**Figure 6.** Evolution of Spearman  $\rho$  rank correlations between the ranking obtained from the calibrated model and the actual values for each category and for editors (upper panel) and articles (middle panel). Corresponding  $\beta$  values are also shown for interest (lower panel). The correlations are generally quite high :  $0.46 < \rho_e < 0.75$  with  $\langle \rho_e \rangle = 0.64$  for editors and  $0.57 < \rho_a < 0.91$  with  $\langle \rho_a \rangle = 0.72$ .  $\rho_a$  is stable over time, which means that the quality of articles can be well captured early on by the model. However,  $\rho_e$  exhibits a convex increase over time, suggesting that it takes time (i.e. lots of edits) to capture well the expertise of editors.

$$w_e^* \sim k_e^{1-\beta} \langle k_a^{-\alpha} \rangle_e w_a^* \sim k_a^{1-\alpha} \langle k_e^{-\beta} \rangle_a \quad (6)$$

Then letting  $\alpha = 0$ , we can simplify to:

$$w_e^* \sim k_e^{1-\beta} w_a^* \sim k_a \langle k_e^{-\beta} \rangle_a \quad (7)$$

Recalling that the variables  $\alpha$  and  $\beta$  control the preferential attachment to move to more connected editor or article nodes in the transition matrix. We will talk about the importance of "super-users" and "super-articles" as those nodes that would be effected greatly by preferential attachment. We concentrate on our unfixed variable,  $\beta$ , as it influences editor ranking ?? and article ranking??. Over all categories and

snapshots we found  $-2 < \beta < 2$ , which has a related spectrum of interpretations. With examples from both ends of the spectrum we find footing to consider  $\beta$  as a proxy for “collaborativeness”.

Consider the highest  $\beta$  found, on category *Sexual acts*. We chose to include this category because it could be considered taboo or perverse to edit these articles. This category’s articles are the least collaboratively edited; the high  $\beta > 1$  means that many edits - albeit very slightly - hurt your ranking ???. While this may seem counter intuitive, an explanation can be seen through the fact that Wikipedia is notable for a vast and constant amount of vandalism and “edit-warring”, which often has a juvenile and lewd nature. Previous Wikipedia research has shown this unintuitive result, that on some articles most active editors exhibit deleting behavior that would lower metric-based article quality ratings [16]. Articles about Sexual Acts, because of their socially-sensitive nature are particularly prone to attracting vandals or edit-warring behavior. Therefore the editors making the most edits are not necessarily the ones improving article quality, as we would typically expect.

This category is at the chaotic end of the Wikipedia spectrum. On the other hand, there are more prime examples of organized activity. Category *Military History of the US* is famous within Wikipedia for its self-organizing task-forces, and at the latest snapshot exhibits  $\beta = 0$ . In fact, it is the only Category that ever have consecutive snapshots where a maximal correlation came from  $\beta < -1$ . The interpretation of  $\beta < -1$  is that article quality is very positively proportional to the number of editors touching the article ???. This is no coincidence, we chose this category, because it has a reputation for being very organized. Military History is a “WikiProject” with a hierarchy of coordinators, an IRC channel, and a mailing list. As a result of the coordination there is less edit-warring and more focused attention in the category. Each visit to the page by good editors has a definite, productive task at hand. This can also be seen by the  $\beta \leq 0$  editor influence ??, that super-users are linearly or super-linearly rewarded in rank for their contributions. It requires a frictionless, collaborative environment where the more you edit, the more and more experienced you become. It’s also worth noting that [3], found that “coordination demands influence the tendency of editors with similar levels of experience to work together”. In our scenario that would mean that the coordination present attracts super-users to work in the productive environment. The category Military History is empirically a standout case of collaboration, and shows in its calibrated  $\beta$  measurements.

Why is the measure beta relevant in the socio-technico world?

From a Wikipedia perspective this collaborativeness measure could be operationalized to aid the problem of finding and retaining new users. New users have historically been driven away because of harsh first encounters with un-collaborative editors. Imagine a program that would suggest to new editors the less antagonistic parts of Wikipedia in which to start editing. In fact placement suggestion programs already exist, such as “Suggestbot” ?? that are used to try and find next articles of interest for an already-active editor. This suggester

would be similar except that it targets friendly Wikipedia categories, and requires no user history. A solution would be to create an feed of the most collaborative categories that a new user could browse through when considering making their first edit. This is a reverse approach from current on-boarding practices, where an interest topic is first chosen and then an edit is made in basically a random-chosen environment. We propose to select the environment first.

Beyond the Wikipedia, corporate private wikis could also use this measurement to classify their employee’s behavior. From a business perspective this algorithm could be run over the entire wiki to produce collaborative results. It could show you how collaborative part, or all of your company wiki is. That statistic could be used to show the health of the wiki’s collaboration. It could even be used as a proxy metric for how collaboratively the company is working, and how much the best quality-making users are the most active.

Overall, it is also practical to run this algorithm on Wiki, because it requires only the binary matrix  $M_{ea}$  and simple counting on histories and articles that are already kept in a wiki. It suggests some kind of parsimonious, *less is more* mechanism, which has direct implications on the overall cost of evaluating contributions in the complex entanglement of contributions. Namely, the use of the bi-partite network random walker model requires only simple and straightforward data mining, compared with, for instance, a model that would primarily rely on the type of words written by editors.

## LIMITATIONS AND FUTURE WORK

The results we have presented in this paper show that contributions – and the value they provide to the collective good – can be effectively disentangled with the bi-partite network random walker model. However, these results suffer from a number of limitations, which call for further work and testing.

According to the original philosophy of the method of reflections [13], an additional node type reflecting *capabilities* should connect producing and produced entities. In the method of reflections, capabilities are implicit in the model, mainly because they are not observable. In the context of Wikipedia and open collaboration, incorporating capabilities would be more feasible. We can for instance identify what an editor do best to improve an article, among the five metrics (ratio of mark-up to readable text, number of headings, article length, citations per article length, and outgoing intrawiki links) we have used to assess the quality of an article.

We believe there are two further directions to improve our results. First, we have followed the philosophy of the method of reflections that aims at ranking countries in the world economy. However, the bi-partite network random walker method provides absolute values, which might have a meaning in the context of open collaboration. In future work, we would like to understand further these absolute values. Second, we took the very simplest information for the input matrix  $M_{ea}$  (i.e. whether an editor has modified a given article, or not). We wonder how the performance of the method might change if richer information is incorporated in the matrix (e.g. number of edits, number of bytes changes). Two exclusive hypothe-



ses could be tested: either the model fits better with richer information, or on the contrary, the model is not as good. In the latter case, we would face a *less is more* scenario, which would require elucidating why less rich information accounts better for reality. Or conversely, it could help further understand what ground-truth metrics actually contain richer information, and hence, help reverse engineer most relevant direct measures of editor expertise and article quality.

As it stands, our method for finding the optimizing pair of control parameters ( $\alpha^*$ ,  $\beta^*$ ) for the *bi-partite network random walker* model is a grid search, because gradient-based optimizers do not handle the singularities that the model produces. Given that computer time required by grid-search grows at the square of the problem (e.g. the size of a category), more work is needed to improve the efficiency of the optimizing algorithm for calibration of  $\alpha$  and  $\beta$ . We can also improve the method to obtain smoother optimization spaces.

## CONCLUSION

We have presented a recursive algorithm based on a *bi-partite network random walker* model, which jointly ranks Wikipedia editors by their expertise, and articles by their quality, from a simple input matrix recording which editor has modified a given article. Moreover, upon calibration on 12 categories of Wikipedia articles, the input and the control parameters of the model inform directly on how value is created from the complex network of contributions. It appears that some categories of Wikipedia articles fully benefit from the multiplicity of contributors (i.e. “collaborativeness”), while for other categories, more contributors per article generate dis-value. The origins of these differences between categories could stem from limited coordination capacity between contributors. The organization of value creation in open collaboration might also be intrinsically different from one type of knowledge to another. Finally, we want to stress the generality of the method we have presented. Similarly to open collaboration in Wikipedia, the proposed algorithm can be applied to a variety of situations, such as social coding (e.g. Github), or collaborative rating (e.g. Amazon or Yelp reviews). Applying the bi-partite network random walker model will help further understand to origins of collective value creation and quality, which are the hallmark of open collaboration.

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