Pushing Your Point of View: Behavioral Measures of Manipulation in Wikipedia

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ABSTRACT

As a major source for information on virtually any topic, Wikipedia serves an important role in public dissemination and consumption of knowledge. As a result, it presents tremendous potential for people to promulgate their own points of view; such efforts may be more subtle than typical vandalism. In this paper, we introduce new behavioral metrics to quantify the level of controversy associated with a particular user: a Controversy Score (C-Score) based on the amount of attention the user focuses on controversial pages, and a Clustered Controversy Score (CC-Score) that also takes into account topical clustering. We show that both these measures are useful for identifying people who try to "push" their points of view, by showing that they are good predictors of which editors get blocked. The metrics can be used to triage potential POV pushers. We apply this idea to a dataset of users who requested promotion to administrator status and easily identify some editors who significantly changed their behavior upon becoming administrators. At the same time, such behavior is not rampant. Those who are promoted to administrator status tend to have more stable behavior than comparable groups of prolific editors. This suggests that the Adminship process works well, and that the Wikipedia community is not overwhelmed by users who become administrators to promote their own points of view.

Keywords

Social networks, Wikipedia, manipulation

1. INTRODUCTION

Wikipedia has become a one-stop source for information on nearly any subject. In aggregate, it has the power to broadly influence public perceptions. Wikipedia's ubiquity creates strong incentives for biased editing, attracting editors with strong opinions on controversial topics. At the same time, Wikipedia is self-policing, and over time the Wikipedia community has formulated a comprehensive set of policies to prevent editors from "pushing" their own points of view on the readership ("POV pushing"). Most policing takes the form of users editing or reverting disputed content, while persistent violations are brought to the attention of administrators. A responding administrator has the power to temporarily protect pages from being edited, and to block users from editing. POV pushing is not considered vandalism on Wikipedia, the latter term being reserved for blatantly ill-intentioned edits.

While there has been a lot of attention paid to the problems of vandalism and maintenance on Wikipedia, there has been little systematic, quantitative investigation of the phenomenon of POV pushing. Nevertheless, anecdotal evidence suggests that it is a serious issue. For example, in April 2008 a pro-Palestinian online publication called Electronic Intifada released messages from the pro-Israel media watchdog group CAMERA (the Committee for Accuracy in Middle East Reporting in America) that asked for volunteers to help "keep Israel related entries ... from becoming tainted by anti-Israel editors." The messages also contained blueprints explaining how members could become Wikipedia administrators, and then use their power to further the goals of the organization [1]. Editors become administrators on Wikipedia by first being nominated, then passing review by a relatively small group of self-selected editors (usually fewer than 100). Typically the group must be at least 80% in favor of the nomination. Administrators can protect pages, block users, and generally serve an important role in conflict resolution.

To further illustrate the importance of the problem, in an interview with Alex Beam of the *Boston Globe*, Gilead Ini, who initiated the CAMERA campaign, said "[Wikipedia] may be the most influential source of information in the world today, and we and many others think it is broken" [2]. But another quote from Ini highlights the difficulty of confronting these issues, "Wikipedia is a madhouse. We were making a good-faith effort to ensure accuracy." Indeed, Wikipedia policies typically assume good faith. The policy on vandalism states "Even if misguided, willfully against consensus, or disruptive, any good-faith effort to improve the encyclopedia is not vandalism. Edit warring over content is not vandalism."[1] In addition to the difficulty of arguing against good faith when editors may simply be attempting to disseminate strongly held beliefs, even more subtle forms of manipulation can achieve a similar outcome. For example, a manipulative administrator may enforce Wikipedia's Neutral Point Of View (NPOV) guidelines selectively, reverting only edits that take a particular point of view. Hypothetically, a manipulative admin with a conservative viewpoint may revert all edits that seem to push a liberal viewpoint, while leaving those that push a conservative viewpoint untouched (or vice versa for a manipulative liberal admin). While there is nothing technically "wrong" with this, it can significantly affect the information

[1] `http://en.wikipedia.org/wiki/Wikipedia:Vandalism` retrieved 11/4/2011.

on pages.

Biographies of living persons have the potential to be particularly divisive. In 2006, there was a significant controversy surrounding edits to Wikipedia pages of prominent U.S. politicians, made by their own staff.[2] It is worth noting that even if there is attempted manipulation on sensitive pages, it is restricted to a relatively small fraction of Wikipedia. Most pages are more "encyclopaedic" in nature (for example, pages on mathematics or on algorithms), and generate less controversy than pages that deal with current events or ideologies.

All of this cries out for a useful algorithmic method of detecting potential POV pushing behavior, and quantitative metrics that can provide evidence and allow us to examine the behavior of such users in more detail. In this paper we present two such metrics and then use them to examine the behavior of the population of administrators.

The first metric, the Controversy Score ("C-Score"), measures the proportion of energy an editor spends on controversial pages. It works by first assigning a controversy score to each page. This score is based on factors that have been identified as well-correlated with controversy, including the number of revisions to an article's talk page, the fraction of minor edits on the talk page, and the number of times it has been protected [9]. It is independent of language or content, and therefore easily generalizable. An editor's C-Score is then the mean of the controversy scores of the pages she edits, weighted by the proportion of her editing attention she focuses on those pages.

While the C-Score is a useful measure, it does not account for the topical clustering of a user's edits. This is particularly important when we use these scores to assess the behavior of administrators, because administrators' responsibilities imply that they will spend more time on controversial pages in general. However, we would expect users who have strong opinions on a topic to push their POV especially in pages related to that topic, rather than broadly across many different controversial topics. Consider two editors A and B, with 100 edits each. They each have 25 edits on the article about the U.S. Republican party. Editor A's remaining edits are about Republican legislators and Republican sponsored legislation from the past 10 years, while B's are divided between the IRA, the Catholic Church, and Jimmy Wales. All of B's edits are controversial, but only some of A's edits are. While B has more controversial edits, we would intuitively consider A to be more suspicious.

To deal with editors of this form, we introduce the Clustered Controversy Score ("CC-Score"), which takes into account the similarity among different pages that a user has edited, in addition to how controversial those pages are. We expect the CC-Score to be particularly useful for triage, as it is designed to be a high recall measure: it flags potentially manipulative users, who focus their attention on specific topic areas that include controversial topics. Of course, some users who have editing patterns of this form may be acting in good faith and just have deep interests in that topic.

Both the C-Score and the CC-score are behavioral. They do not rely in any way on the specific text of edits, only on the patterns of editing. We demonstrate the validity of the two scores by showing that they have predictive power in discriminating between heavy editors who were blocked and equally heavy editors who were not. Having validated them on an exogenous measure, we then apply these measures in order to analyze the behavior of administrators. We compare the editing patterns of administrators who score highly on the C-Score and the CC-Score. The CC-Score identifies administrators who would not have been identified by the simple C-Score, because only some of the major pages on the topics they edit are highly controversial. These administrators also edit a long tail of related pages, thus influencing public perception of the topic at large.

Finally, we use the CC-Score to test whether or not admins are behaving in a truly manipulative manner: first becoming trusted and attaining promotion to admin status, and then using this trusted status to push their points of view in particular domains. To do so, we look at changes in CC-score before and after the editor stood for promotion (the Request for Adminship, or "RfA" process). While we find several instances of potentially suspicious changes of focus, we also note that the overall behavior of the population of editors who become admins is better than that of two comparable populations: (1) those who stood for election but failed; and (2) those who edited prolifically but never stood for election to administrator status. The population behavior is better in the sense that the variance of changes in the CC-Score pre- and post-RfA is lower, indicating that those who fail in their RfAs actually change their behavior more significantly. Thus, Wikipedia admins as a population do not misrepresent themselves in order to gain their trusted status.

1.1 Contributions

We introduce two new behavioral measures that indicate whether or not a user is trying to push his or her point of view on Wikipedia pages. These measures have predictive power on historical data: they can determine which users were blocked for disputes related to controversial editing. We anticipate that these measures can be used for auditing or triage: they can flag potentially suspicious behavior automatically for more detailed human investigation. The measures are behavioral and general, and do not rely on specifics of text edited by users, and are thus applicable beyond Wikipedia.

We then show how these measures can be used to discover interesting changes in behavior, focusing on the behavioral changes of editors who applied for promotion to administrator status on Wikipedia. While there are instances of suspicious looking changes in behavior upon promotion to administrator status, we find that at the population-level, Wikipedia editors are in fact better behaved than the population of prolific editors, in the sense that their behavior is more stable, and does not change significantly upon promotion. While there are specific instances that seem suspicious, our evidence suggests that the Wikipedia adminship process works well at the population level: there is no evidence that editors are in general seeking promotion to adminship so they can "push" their point of view on the larger population.

2. RELATED WORK

There is a large literature on many different aspects of Wikipedia as a collaborative community. It is now well-established that Wikipedia articles are high quality [5] and very popular on the Web [15]. The dynamics of how articles become high quality and how information grows in collective media like Wikipedia have also garnered some attention [18, 4]. While there has not been much work on how Wikipedia itself influences public opinion on particular topics, it is not hard to draw the analogy with search engines like Google, which have the power to direct a huge portion of the focus of public attention to specific pages. Hindman *et al.* discuss how this can lead to a few highly ranked sites coming to dominate political discussion on the Web [6]. Subsequent research shows that the combination of what users search for and what Google directs them to may lead to more of a "Googlocracy" than the "Googlearchy" of Hindman *et al.* [12].

Our work in this paper draws directly on three major streams of literature related to Wikipedia. These are, work on conflict and

[2] `http://en.wikipedia.org/wiki/Congressional_Staffer_Edits` retrieved 11/4/2011.

controversy, automatic vandalism detection, and the process of promotion to adminship status on Wikipedia.

There is a significant body of work characterizing conflict on Wikipedia. Kittur *et al.* introduce new tools for studying conflict and coordination costs in Wikipedia [9]. Vuong *et al.* characterize controversial pages using both disputes on a page and the relationships between articles and contributors [16]. We use the measures identified by Kittur *et al.* and Vuong *et al.* as a starting point for measuring the controversy level associated with a page. This then feeds into our user-level C-Score and CC-Score measures. Our results on the blocked users dataset serve as corroborating evidence for the usefulness of these previously identified measures. Conflict on Wikipedia is traditionally resolved by appealing to outside sources. However, Lopes *et al.* [11] find that accessibility issues significantly impede this process. Welser *et al.* [17] identify social roles within Wikipedia: substantive experts, vandal fighters, social networkers, and technical editors

Automatic vandalism detection has been a topic of interest from both the engineering perspective (many bots on Wikipedia automatically find and revert vandalism), as well as from a scientific perspective. Potthast *et al.* [13] use a small number of features in a logistic regression model to detect vandalism. Smets *et al.* report that existing bots, while useful, are "far from optimal", and report on the results of a machine learning approach for attempting to identify vandalism [14]. They conclude that this is a very difficult problem to solve without incorporating semantic information. While we touch on vandalism in dealing with blocked users, we are focused on "POV pushing" by extremely active users who are unlikely to engage in petty vandalism, which is the focus of most work on automated vandalism detection.

Wikipedia administrator selection is an independently interesting social process. Burke and Kraut study this process in detail and build a model for which candidates will be successful once they choose to stand for promotion and go through the Request for Adminship (RfA) process [3]. The dataset of users who stand for promotion is useful because it allows us to compare both previous and later behavior of users who were successful and became admins and those who did not.

Finally, we use a similarity metric for articles based on editors which is similar to existing work on expert-based similarity [10].

3. METHODOLOGY

We begin by discussing our methodology in computing the "simple" Controversy Score for each user, and then describe how we can compute a Clustered Controversy Score that captures editors who focus on articles related to a single, controversial topic.

All data is from an April 2011 database dump of the English Wikipedia. The term "article" refers to a page in Wikipedia's article namespace along with any pages in the article talk namespace with the same name, unless otherwise specified.

3.1 Controversy Score

We define the C-Score for a user as an edit-proportion-weighted average of the level of controversy of each page. The controversy of a page (loosely following the article-level conflict model of Kittur *et al.* [9]) is based on the number of revisions to an article's talk page, the fraction of minor edits on an article's talk page, mentions of "POV" in edit comments, and the number of times a page is "protected", where editing by new or anonymous users is limited.

We scale and shift each of the four quantities above such that their 5th and 95th percentiles are equal, then take the mean. Next, we transform this number such that the lowest values are at -5 and 1% of articles have scores above 0. Finally, the scores are transformed using the logistic function $1/(1+e^{-t})$. This produces a controversy score $c_k \in [0,1]$ for each page.

One alternative to uniform weighting is logistic regression, where a model is trained on a data set reflecting some notion of controversy. Deciding which of the four measures should be more important in the absence of such an extrinsic weighting seems like a very difficult problem: should a page with lots of "POV" mentions but no protections or talk page edits be ranked higher than a page which has been protected many times, but has no talk page edits or mentions of "POV"? In practice, weighting has very little effect on which pages we designate as very controversial: highly controversial pages by one metric tend to be controversial by other metrics as well. For example, the average percent rank of the controversy score for articles with six mentions of "POV" in edit comments is above 99, while a page with six mentions of "POV" but no protections or talk page edits only has a percent rank of 97. This is a very intuitive phenomenon: pages where content is repeatedly disputed ("POV" in edit comments) but none of the editors discuss the dispute (talk page edits) are very rare. Likewise for articles with three protections, or articles with 75 talk page edits, despite neither of these factors alone being sufficient for a 99$^{\text{th}}$ percentile controversy score.

Let p_k be the fraction of a user's edits on page k. The controversy score for a user is then an edit-weighted average of the page-level controversy scores:

$$\text{CScore} = \sum_k p_k c_k \tag{1}$$

We would expect this measure to be effective at finding users who edit controversial pages. However, many Wikipedia users dedicate at least part of their time to removing blatant vandalism, which occurs disproportionally on controversial pages. Thus we turn to a measure that combines topical clustering with controversy.

3.2 Clustered Controversy Score

We work from the hypothesis that users who concentrate their edits have some vested interest in those articles. Going back to the example in the Introduction, we would like to be able to detect users like A, who focuses almost entirely on Republican politics. While A's edits include some controversial pages, B fights vandalism broadly, and so has exclusively controversial edits. B has the same number of edits to the article on the U.S. Republican Party as A, but the rest of B's edits are scattered across other topics. A's edits to this article are interesting; they are topically related to A's other edits. At the same time, edits to this article by editor B are far less interesting.

We would like to incorporate a measure of topical edit concentration into the C-Score. In order to do so, we could define topics globally, but this is both expensive and sensitive to parameter changes: what is the correct granularity for a topic? Instead, we focus on a local measure of topical concentration. Given a similarity metric between articles, we can measure the extent to which a user's edits are clustered.

Page similarity.

We base our score on a generalization of the clustering coefficient to weighted networks with edge weights between 0 and 1 [8]. Several natural measures of page similarity have values in this rage.

We consider pages which link to (or are linked from) the same pages as similar, pages edited by the same users as similar, and pages in the same categories as similar. While controversy tends to saturate, with highly controversial pages by one metric also being controversial by others, this is not true of page similarity in general.

Pages can be similar in many independent ways. For instance, disambiguation pages in Wikipedia share several administrative categories, and are often edited by a similar set of users. However, we would still like disambiguation pages which link to pages in common (for example, “Washington” and “DC”) to be more similar by our metric than those which don’t. This leads us to a linear combination of disparate similarity measures, rather than the saturation model we use for controversy.

Each page has a set of incoming links I, outgoing links Θ, users U, and categories Γ associated with it. To determine how similar two pages are based on one of these sets, we divide the cardinality of the intersection of the sets from each page by the cardinality of their union (the Jaccard coefficient). To compute a single similarity score between two pages i and j, we take an average of scores for each type of set, giving equal weight to links, users, and categories. The similarity score w_{ij} is then:

$$w_{ij} = \frac{1}{6}\frac{|I_i \cap I_j|}{|I_i \cup I_j|} + \frac{1}{6}\frac{|\Theta_i \cap \Theta_j|}{|\Theta_i \cup \Theta_j|} + \frac{1}{3}\frac{|U_i \cap U_j|}{|U_i \cup U_j|} + \frac{1}{3}\frac{|\Gamma_i \cap \Gamma_j|}{|\Gamma_i \cup \Gamma_j|} \quad (2)$$

The particular weights assigned to each similarity measure are largely irrelevant. We have two main goals when calculating w_{ij}. First, we want pages which are not similar in any sense to have very low similarity scores. This is true of most pages under any weighting: the average w_{ij} (where a single user has edited both i and j) is about 0.01. Second, pages which are similar in more ways should have higher scores; a uniform weighting is the simplest way to achieve this.

Several of the scores we combine to measure page similarity are simpler versions of popular metrics. For example, SimRank [7] is often used to measure structural similarity; we use only first-order link information here. Likewise, expert based similarity [10] takes the number of edits by a user on a given page into account. Category information is sometimes used to validate such similarity metrics on Wikipedia. For our purposes, refined similarity measures are unnecessary: we rely only on aggregate similarities when computing scores for a given user, and are most interested in using these scores to determine relative rankings. The CC-Score is applicable even in domains without Wikipedia’s meta-data, where rich similarity measures may not be available.

Computing the CC-Score.

Consider a set of edits from a user. Let N be the number of unique pages in this set and w_{ij} be the similarity score between pages i and j. We start with a generalization of the clustering coefficient [8]. For a page k, define:

$$\mathrm{clust}(k) = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ki}w_{kj}w_{ij}}{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ki}w_{kj}} \quad (3)$$

The clustering coefficient will be higher when other pages in the edit set are related to k and to each other. When computing the CC-Score for the entire edit set, there are two other factors we would like to consider: how much a user concentrated on any given page, and how controversial that page is. Let p_k be the proportion of edits on page k, and c_k be some measure of controversy. Then we have the following coefficient for the edit set:

$$\mathrm{CCScore} = \sum_{k=1}^{N} p_k c_k \mathrm{clust}(k) \quad (4)$$

Since $\sum_{k=1}^{N} p_k = 1$, (4) is a weighted average. If $c_k \in [0,1]$, then so is (4). Pushing raw controversy scores through a sigmoid to produce c_k ensures that this condition holds, and also prevents outliers from unduly affecting the final score.

There is no reason that c_k must be a measure of controversy. Instead, it can measure any property of a page which is of interest. For example, a c_k measuring how much a page relates to global warming would yield a ranking of editors based on the extent to which their edits concentrate on global warming. The CC-Score is a general tool for ranking single-topic contributors based on some property of that topic. We also compute a raw Clustering Score where each page has $c_k = 1$ in (4) – this yields a measure of topical clustering independent of any properties of the particular pages.

We choose a measure that combines clustering and controversy page-wise rather than user-wise so that we do not end up with editors who are very topically focused on uncontroversial pages (say Flamingos), but also spend a significant fraction of their time combating vandalism broadly across a spectrum of topics. We also note that the only Wikipedia-specific contributions to the CC-Score are encapsulated in the computation of c_k and w_{ij}. The same quantities can be computed for a wide variety of collaborative networks. Consider email messages: w_{ij} between two threads could be based on senders and recipients, and c_k based on the length of the thread as a measure of controversy. These quantities are entirely language independent, although we might make use of natural language processing to improve estimates of both similarity and controversy.

4. EVALUATION

We evaluate our metrics in several different ways. First, to establish their validity, we examine whether the metrics provide discriminatory power in identifying manipulative users. In order to do so, we need an independent measure of manipulation, so we focus on users that were blocked from editing on Wikipedia, and compare them with a similar set who were not blocked. One of the goals of our work is to provide an objective metric for analyzing administrators, who have gained significant status in Wikipedia. We present some detail on the editing habits of the admins who score highest on our metrics. In doing so, we also use our metrics to provide fresh insight into what is controversial on Wikipedia, by analyzing the topic distribution of edits amongst admins with high CC-Scores.

A reasonable hypothesis, suggested by the CAMERA messages discussed in Section 1 is that people who wish to seriously push their points of view on Wikipedia may try to become admins by editing innocuously, and then changing their behavior once they become admins. In order to examine this hypothesis, we look at the behavior of admins whose CC-Scores changed significantly, as well as at the distribution of changes in the CC-Score.

4.1 Blocked users

Users can be blocked from Wikipedia for a variety of reasons. Reasons for blocks include blatant vandalism (erasing the content of a page), editorial disputes (repeatedly reverting another user’s edits), threats, and more. Many blocks are of new or anonymous editors for blatant vandalism; we are not interested in these blocks.

We are interested in blocks stemming from content disputes. While editors are not directly blocked for contributing to controversial articles, controversy on Wikipedia is often accompanied by “edit warring”, where two or more editors with mutually exclusive goals repeatedly make changes to a page (e.g., one editor thinks the article on Sean Hannity should be low priority for WikiProject Conservatism, and another thinks it should be high priority).

We examine a set of users who were active between January 2010 and April 2011. For blocked users, we use 180 days of data, directly before the block. For the users who were never blocked, the 180 days ends on one of their edits chosen randomly. In order to filter out new or infrequent editors, we only consider users with between 500 and 1000 edits during this 180 day period. The

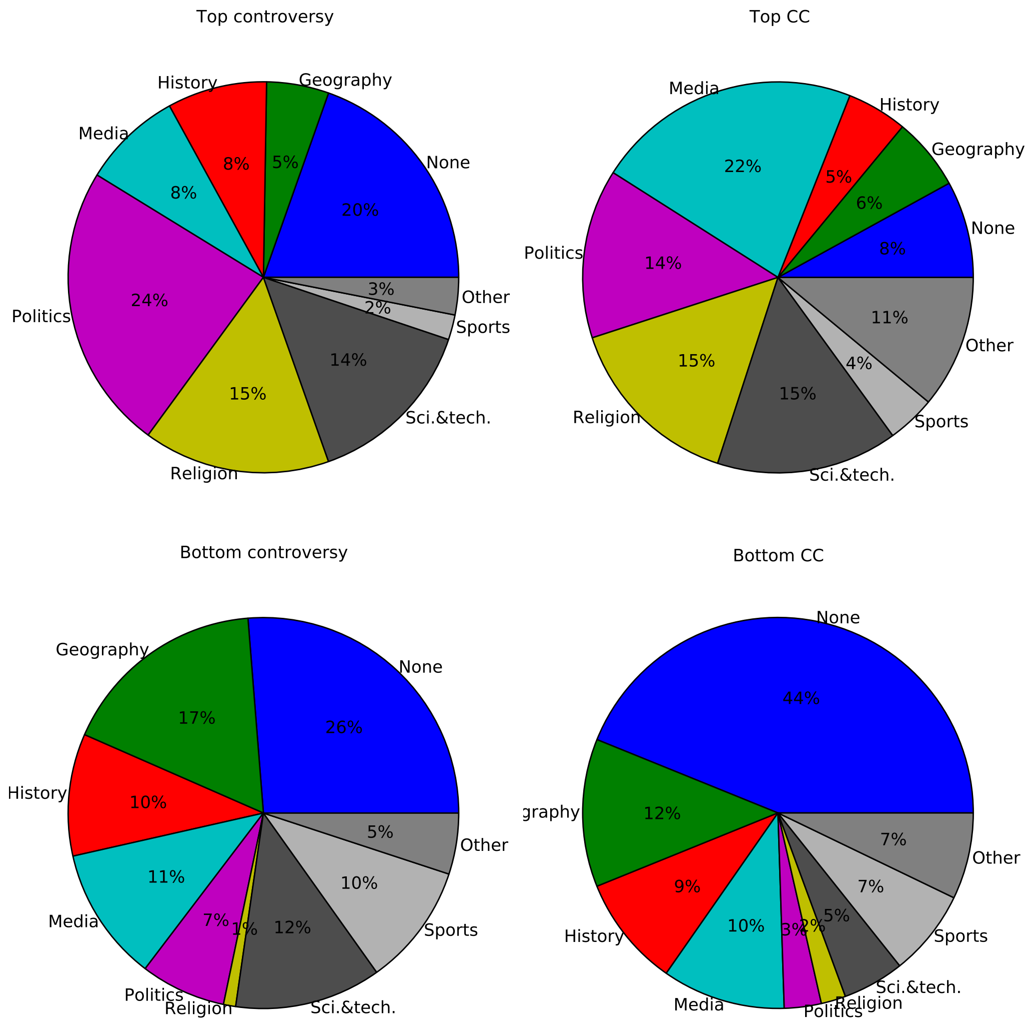


Figure 2: Human evaluation of the general category of edits (if any) for administrators directly after their RfA. The 100 highest and 100 lowest scoring administrators for each metric are shown; because of overlap, 286 administrators are represented in total. Many users with a high CC-Score are topically focused, and the CC-Score finds many more media-focused users than the C-Score.

upper bound removes users who do significant amounts of automated editing; it is not uncommon for such accounts to be blocked for misbehaving scripts which have nothing to do with controversy. By examining only exceptionally active users, we eliminate most petty reasons for blocks: users who have made hundreds of legitimate contributions are unlikely to start blatantly vandalizing pages. Finally, we only examine users who were blocked for engaging in point of view pushing: edit warring, 3 revert rule violations, sock puppets (creating another account in order to manipulate), and violations involving biographies of living persons. These users constitute the majority of those blocked (143 of 178). After the filtering, we are left with 143 blocked users and 236 who were never blocked.

Figure 1 shows the performance of the CC, Controversy, and Clustering Scores when discriminating between the blocked users and users who were never blocked. Both the CC- and C-Scores show significant discriminative power, while Clustering alone is no better than guessing.

The performance of the CC- and C-Scores on the blocked users data set validates both measures for detecting users who make controversial contributions to Wikipedia. Many blocks in this data set involve violations of Wikipedia's "3 Revert Rule", limiting the number of contributions which an editor can revert on a single page during any 24 hour period, which implies that editors are not only making controversial changes but are vigorously defending them. This rule is not automatically enforced and does not apply to blatant vandalism; instead, another user must post a complaint which is then reviewed by an administrator. The discriminative power of the CC- and C-Scores in detecting this and other types of point of view pushing provides strong evidence that these scores are correctly detecting controversial editors.

4.2 Highest scoring admins

We now turn to examining the behavior of admins through the lens of the Controversy and CC-Scores. Where do admins focus their attention, and what is controversial on Wikipedia? To explore

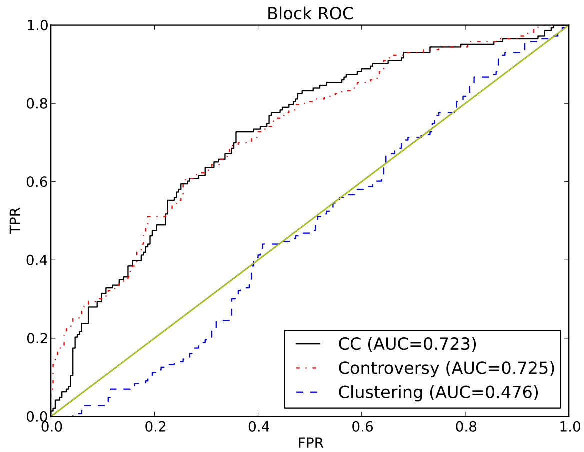


Figure 1: ROC curve for CC, Controversy, and Clustering Scores when differentiating between blocked and not-blocked users, based on 180 days of data. The CC and Controversy Scores effectively discriminate between these classes, whereas the Clustering Score does not; there is no significant difference between the CC and Controversy Score curves. The curve indicates the true positive (TPR) at a given false positive rate (FPR) at different thresholds, when classifying each user as either blocked or not blocked. Area under the ROC curve (AUC) indicates how discriminative the scores are, and is the probability that a random blocked user is ranked higher by the given score than a random non-blocked user.

this issue, we use human evaluations of the edit history of administrators during the 180 days after they became an administrator. Without knowing anything about the CC, Controversy, or Clustering Scores associated with the edit history, a reviewer analyzed the top 50 pages edited by a user and decided which general category, if any, the edits were in. Results for the top and bottom 100 administrators ranked by each score are presented in Figure 2.

Figure 2 is useful validation for our methodology: for example, administrators with very low CC-Scores were often classified as not editing in a coherent general category. Conversely, users with a high CC-Score were much more likely to be topically focused. This effect is even more apparent for the raw Clustering Score, with 73% of the bottom 100 admins classified as topically unfocused. This implies that our article similarity metric corresponds with an intuitive notion of topical similarity.

There are some interesting differences in the topic areas of the 100 admins with the highest C-Scores and the 100 with the highest CC-Scores. As expected, the C-Score picks up a substantial chunk of editors with no particular focus, while the CC score does not. These are admins who are doing their job of "policing" controversy across a broad spectrum of topics. Surprisingly, the C-Score picks up more politically focused editors while the CC-Score picks up many more who focus on media and entertainment.

Specific examples help to elucidate this effect. Table 1 shows the top 6 administrators by CC and C-Score respectively for the 180 day period immediately following their promotion (successful RfA). The CC-Score picks up three media-focused editors while the C-Score does not. These editors focus on a specific media franchise (a TV show, for example), editing on this topic almost exclusively. The long tail of edits for media-focused users often includes non-controversial articles related to the same media franchise, for example articles on minor characters. This comprehensive long tail means that the page-level clustering score for pages related to the media franchise is very high, including the main pages related to the franchise; these main pages tend to be quite controversial. This combination of controversy and clustering contributes significantly to the user's overall CC-Score, while the long tail of less controversial articles moderates the C-Score.

We note that all the users with very high C-Scores also have very high CC-Scores (falling at least in the 96th and typically in the 99th percentile of CC-Score). However, the converse is not true, because of the properties of the CC-Score described above. For example Admins 3, 4, and 5 in particular are relatively low in C-Score. Admin 5 is media-focused. Admin 4 has a high CC-Score despite editing topically unrelated pages; yet the similarity scores between them are high. This user focuses on disambiguation pages, all of which share common categories, and many of which are maintained by the same users. Major disambiguation pages also turn out to be fairly controversial, being of interest to editors contributing to any of the pages they link to. This combination of a long tail of "related" disambiguation pages with controversial major disambiguation pages leads to a high CC-Score, just as it did for media. As with media, the CC-Score highlights a real phenomenon on Wikipedia: WikiProject Disambiguation, of which this user is a member, consists of users who focus their efforts on disambiguation pages. Thus the CC-Score is finding exactly single-topic editors of controversial pages, even if their topic is rather specific to Wikipedia.

The story with Admin 3 is similar to Admins 4 and 5, in that this editor also edits a long tail of uncontroversial articles. Qualitatively, it is useful that the CC-Score is picking up different people than the simple C-Score, and sometimes turning up surprises – this is exactly the kind of behavior one would want to pick up on, and it may give the CC-Score an advantage over the simple C-Score in terms of detecting subtle manipulation.

We note that in this paper we are agnostic to what makes a page or a topic controversial, which reveals much of interest about Wikipedia, but at the same time our methods are completely general – specifically, we expect they would work well with any measure of controversy, and so the techniques can easily be adapted to domain-specific needs. For example, to focus on more traditionally controversial single-topic editors, we might consider a modification of the page-level controversy score which ignores controversy on media-related pages. More generally, the page-level controversy score can give preference to any topic; it does not need to be related to controversy at all. For example, we could find single-topic editors interested in a specific country.

4.3 Distribution of CC changes

While it is interesting to find editors focused on a single, controversial topic, it is not surprising that such editors exist; Wikipedia certainly needs domain experts even on controversial topics. Sudden changes in behavior, especially increases in the topical concentration or the controversial nature of edits, are more surprising; especially so when some level of community trust is involved, as with administrators. In particular, an editor changing behavior dramatically shortly after becoming an admin is suspicious.

The RfA process.

Standing for promotion to adminship on Wikipedia is an involved process.[3] An editor who stands for, or is nominated for adminship must undergo a week of public scrutiny which allows the commu-

[3] `http://en.wikipedia.org/wiki/Wikipedia:Rfa`

Admin1

CC 100.0% Clust. 96.4% Cont. 99.9%

Title	Edit%	Cont.
Jehovah's Witnesses	63.9%	100.0%
Salt	6.6%	99.7%
Tony Blair	1.6%	100.0%
Joseph Franklin Rutherford	1.6%	99.7%
Robby Gordon	1.6%	96.4%
Leet	1.6%	100.0%
Jehovah's Witnesses and congregational discipline	1.6%	99.5%
Wavelength (disambiguation)	1.6%	0.0%
Charles Taze Russell	1.6%	100.0%

Admin2

CC 99.9% Clust. 97.4% Cont. 95.7%

Title	Edit%	Cont.
Sailor Venus	4.2%	99.7%
Sailor Moon (character)	4.0%	99.9%
Sailor Mercury	3.7%	99.8%
List of minor Sailor Moon characters	3.1%	99.7%
List of Sailor Moon episodes	3.0%	99.8%
The Church of Jesus Christ of Latter-day Saints	2.7%	100.0%
Sailor Starlights	2.7%	99.6%
Sailor Jupiter	2.6%	99.6%

Admin3

CC 99.9% Clust. 98.8% Cont. 76.6%

Title	Edit%	Cont.
Global city	2.8%	99.9%
List of school pranks	2.6%	99.7%
Scholars for 9/11 Truth	2.0%	99.9%
Pi	1.9%	100.0%
9/11 Truth movement	1.8%	100.0%
Christopher Langan	1.8%	99.9%
Hubbert peak theory	1.8%	100.0%
Stephen Barrett	1.6%	100.0%
Prime number	1.2%	99.9%

Admin4

CC 99.8% Clust. 99.9% Cont. 37.9%

Title	Edit%	Cont.
Matrix	5.4%	96.5%
Apartheid (disambiguation)	3.5%	99.8%
ETA (disambiguation)	3.5%	99.4%
Gemini	3.1%	92.8%
Solo	3.1%	59.0%
XXX	3.1%	96.8%
X Games	2.7%	96.9%
FAST	2.3%	39.2%
Fame	2.3%	74.7%

Admin5

CC 99.8% Clust. 99.3% Cont. 72.3%

Title	Edit%	Cont.
Meet Kevin Johnson	14.7%	98.8%
The Other Woman	10.1%	97.8%
Lost (season 4)	7.2%	99.6%
Lost (season 5)	6.8%	99.3%
List of Heroes episodes	6.2%	99.9%
Martin Keamy	5.3%	96.9%
The Shape of Things to Come (Lost)	4.0%	98.3%
Through the Looking Glass (Lost)	1.8%	99.6%
There's No Place Like Home	1.7%	98.0%

Admin6

CC 99.7% Clust. 95.1% Cont. 83.5%

Title	Edit%	Cont.
Big Brother 2007 (UK)	17.6%	100.0%
List of Big Brother 2007 housemates (UK)	6.7%	98.9%
Ionic bond	6.1%	98.4%
Big Brother (UK)	3.0%	99.9%
Big Brother 8 (U.S.)	2.4%	100.0%
Big Brother X	2.4%	38.8%
Big Brother 2006 (UK)	2.4%	100.0%
Big Brother (TV series)	2.4%	99.8%

Admin7

CC 100.0% Clust. 96.4% Cont. 99.9%

Title	Edit%	Cont.
Jehovah's Witnesses	63.9%	100.0%
Salt	6.6%	99.7%
Tony Blair	1.6%	100.0%
Joseph Franklin Rutherford	1.6%	99.7%
Robby Gordon	1.6%	96.4%
Leet	1.6%	100.0%
Jehovah's Witnesses and congregational discipline	1.6%	99.5%
Wavelength (disambiguation)	1.6%	0.0%
Charles Taze Russell	1.6%	100.0%

Admin8

CC 99.6% Clust. 89.6% Cont. 99.8%

Title	Edit%	Cont.
Global warming	9.7%	100.0%
Global warming controversy	5.6%	100.0%
Electronic voice phenomenon	3.6%	100.0%
An Inconvenient Truth	3.3%	100.0%
Greenhouse effect	3.0%	100.0%
American Enterprise Institute	2.9%	99.8%
The Great Global Warming Swindle	2.8%	100.0%
List scientists opposing the mainstream scientific assessment of global warming	2.8%	100.0%

Admin9

CC 99.5% Clust. 87.5% Cont. 99.8%

Title	Edit%	Cont.
1948 Palestinian exodus	6.8%	100.0%
Yasser Arafat	6.3%	100.0%
Israeli West Bank barrier	4.9%	100.0%
Israeli settlement	4.9%	100.0%
Hebron	4.6%	100.0%
Second Intifada	3.2%	100.0%
Gaza Strip	3.2%	99.9%
Palestinian territories	2.9%	100.0%
Palestinian people	2.9%	100.0%

Admin10

CC 96.3% Clust. 52.1% Cont. 99.7%

Title	Edit%	Cont.
Rick Reilly	10.0%	99.6%
Keith Olbermann	6.4%	100.0%
Lara Logan	5.5%	99.9%
Treaty of Tripoli	4.5%	99.9%
Glenn Greenwald	3.6%	99.9%
Eli Whitney, Jr.	3.6%	99.3%
Michael J. Fox	3.6%	99.8%
Newton's laws of motion	3.6%	99.9%
William Connolley	2.7%	100.0%

Admin11

CC 96.9% Clust. 59.6% Cont. 99.6%

Title	Edit%	Cont.
Abortion	36.6%	100.0%
University of Michigan	5.5%	99.9%
Jesus	3.4%	100.0%
Islamofascism	2.8%	100.0%
NARAL Pro-Choice America	2.8%	99.0%
Intelligent design	2.8%	100.0%
Saint Joseph	2.1%	99.9%
C. S. Lewis	2.1%	100.0%
God	1.4%	100.0%

Admin12

CC 97.7% Clust. 69.3% Cont. 99.6%

Title	Edit%	Cont.
Yasser Arafat	5.2%	100.0%
Estimates of the Palestinian Refugee flight of 1948	2.7%	99.6%
Israel	2.2%	100.0%
ArabIsraeli conflict	2.0%	100.0%
Ariel Sharon	1.8%	100.0%
Jews	1.8%	100.0%
Antisemitism	1.5%	100.0%
Muhammad al-Durrah incident	1.5%	100.0%
Second Intifada	1.5%	100.0%

Table 1: The most edited articles by the administrators with the highest CC-Scores (top 6) and highest C-Scores (bottom 6) during the 180 days after they became an admin. Each article is annotated with the percentile of its article-level controversy score and the percentage of the administrator's edits which were to that article. On top of each table are the percentiles for the CC, Clustering, and C-Scores of the administrator during the same period.

Admin 1: Rank 1

Before RfA Article	Edit%	After RfA Article	Edit%
Jehovah's Witnesses	48.5%	Jehovah's Witnesses	62.1%
Eschatology of Jehovah's Witnesses	3.8%	Jehovah's Witnesses and the United Nations	6.8%
Jehovah's Witnesses practices	2.1%	Criticism of Jehovah's Witnesses	4.9%
Organizational structure of Jehovah's Witnesses	1.6%	Salt	3.9%
Criticism of Jehovah's Witnesses	1.5%	Jehovah's Witnesses and congregational discipline	2.9%
History of Jehovah's Witnesses	1.4%	Eschatology of Jehovah's Witnesses	1.9%
Christianity	1.3%	Blue link	1.0%
Controversies regarding Jehovah's Witnesses	1.1%	Brendan Loy	1.0%
		Charles Taze Russell	1.0%

Admin 2: Rank 3

Before RfA Article	Edit%	After RfA Article	Edit%
Chiropractic	6.5%	Global city	3.9%
Extreme physical information	3.6%	Christopher Langan	2.3%
Prime number	3.4%	Stephen Barrett	2.0%
Normal number	3.2%	Scholars for 9/11 Truth	1.9%
Axiom of choice	3.1%	List of school pranks	1.8%
Year 10,000 problem	2.2%	The National Council Against Health Fraud	1.7%
Difference operator	2.0%	9/11 Truth movement	1.6%
Kenny Rogers Roasters	1.7%	Quackwatch	1.6%
Selector calculus	1.7%	Pi	1.5%

Admin 3: Rank 5

Before RfA Article	Edit%	After RfA Article	Edit%
Rechargeable battery	8.0%	Buddhahood	13.2%
Flywheel energy storage	6.5%	Sri Lanka and state terrorism	3.9%
Ethanol fuel	3.0%	Premier of the Republic of China	3.0%
Imaginary color	3.0%	Sri Lankan Tamil militant groups	2.8%
Mensural notation	2.7%	Outpost for Hope	2.6%
Noise pollution	2.5%	Sri Lanka Armed Forces	2.6%
Pay it forward	2.1%	Liberation Tigers of Tamil Eelam	2.1%
TamilNet	1.8%	Esperanto	1.4%
CIE 1931 color space	1.6%		

Admin 4: Rank 9

Before RfA Article	Edit%	After RfA Article	Edit%
Biman Bangladesh Airlines	8.4%	Mawlid	20.0%
Fatimah	6.3%	Fatimah	11.8%
First Solution Money Transfer	3.0%	Five Pillars of Islam	3.6%
72 Virgins	1.8%	Air Sylhet	3.0%
2007 Bangladesh cartoon controversy	1.3%	Ezra	2.5%
Ramadan	1.2%	Hajj	2.1%
Royal Bengal Airline	1.2%	Osmani International Airport	2.0%
Criticism of the Qur'an	1.2%	Biman Bangladesh Airlines	1.8%
Air Sylhet	1.1%	Eid ul-Fitr	1.8%

Table 2: Most edited articles for 180 days before/after becoming an admin. Users were selected from the top ten in order to show different types of CC-Score changes.

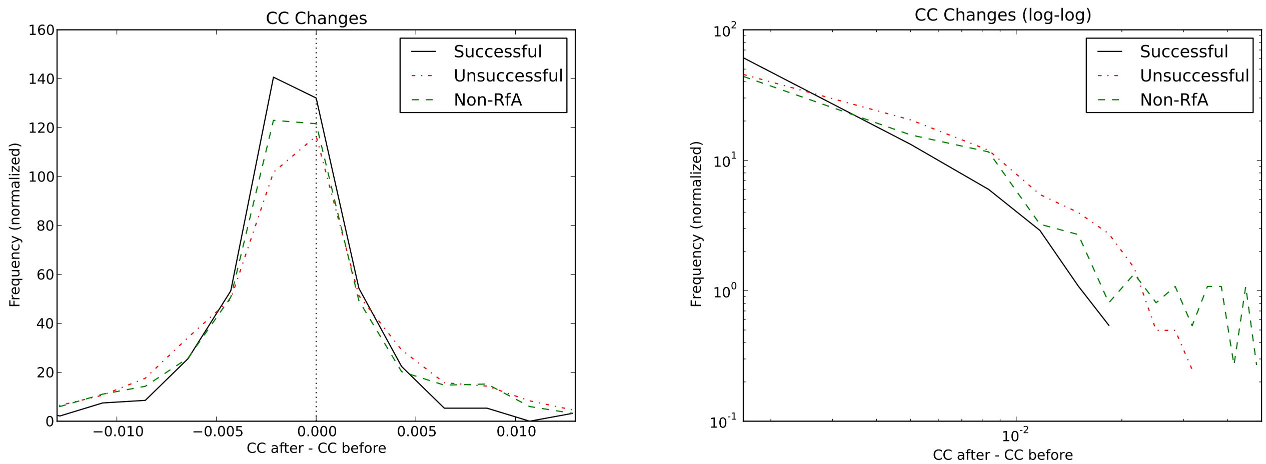
nity to build consensus about whether or not the candidate should be promoted. A special page is set up on which the candidate makes a nomination statement about why she or he should be promoted, based on detailed evidence from their history of contributions to Wikipedia. Other users can then weigh in and comment on the case, and typically a large volume of support (above 75% of commenters) as well as solid supporting statements from other editors are necessary for high-level Wikipedia "bureaucrats" to approve the application. Burke and Kraut provide many further details on this process [3]. Wikipedia policies call for nominees to demonstrate a strong edit history, varied experience, adherence to Wikipedia policies on points of view and consensus, as well as demonstration of willingness to help with tasks that admins are expected to do, like building consensus. Burke and Kraut note that the actual value of some of these may be mixed: participating in seemingly controversial tasks like fighting vandalism or requesting admin intervention on a page before becoming an admin actually seems to hurt the chances of success.

Overall, the Wikipedia community devotes significant effort to the RfA process, and there is a lot of human attention focused on making sure that those who become admins are worthy of the community's trust. Now we turn to examining some cases where the behavior of an editor changed significantly right after they became an admin.

Changes in behavior.

Table 2 shows the article edit history of four administrators for 180 days before and 180 days after their successful RfA. These users were among the top 10 administrators ranked by the change in CC-Score between the two periods (Admins 1, 2, 3, and 4 were ranked 1, 3, 5, and 9 respectively in CC-Score change). For two of the administrators shown (Admin 1 and Admin 4), the change in CC-Score is explained by a change in edit distribution; while the general category of their edits remains consistent, they concentrated on this category much more heavily after their respective RfAs.

For Admins 2 and 3 in Table 2, the change in CC Score is the result of a rather dramatic shift in topic. Admin 2 shifts from mathematics to 9/11 conspiracy theories (several related pages are not shown in the table), while Admin 3 shifts from relatively unfocused edits to the Sri Lankan Civil War. Upon further examination of their behavior, neither administrator appears to be violating Wikipedia policy (instead acting as mediators and enforcing a neutral point of view), and yet the changes are quite striking. While it may not be the case for these editors, a similar pattern could reflect subtle manipulation by one-sided enforcement of the NPOV guidelines, for



(a) Full distribution

(b) Log-log plot of the right hand tail

Figure 3: Distribution of changes in the CC-Score before and after successful and unsuccessful RfAs, and for users who have never participated in an RfA. Although the peaks for successful and (to a lesser extent) non-RfA distributions are slightly negative, the mean is not significantly negative in either case. (b) The distribution for successful RfAs has a lighter tail.

example.

Population-level changes.

This leads us to a more general question. Is there evidence of a population-wide change in Admin behavior after successful RfAs? Figure 3 shows the distribution of CC-Score changes for RfA candidates, both successful and unsuccessful, before and after their respective RfAs (again 180 days each), and for a group of 1000 active editors who were never nominated for administrator status. The results clearly show that those who stand for promotion and are successful behave differently at the population-level than those who either stand for promotion and fail or those who never stand for promotion at all. In fact, they end up staying closer to their previous behavior than either of the other groups – the variance in CC-Score changes is higher for the other two groups than it is for editors who had successful RfAs (see below for details on the data and statistical tests). This implies strongly that there is no serious problem of people becoming admins on Wikipedia in order to push their own point of view. There are two reasonable hypotheses that may explain the lower variance in CC-Score changes for successful RfA candidates. Either some aspect of the RfA process selects for editors who are less likely to change their behavior, or the very fact of becoming an administrator has a "centralizing" influence: given their new status, associated with a (real or perceived) higher level of scrutiny, administrators become less likely to change their behavior.

The hypothesis that the RfA process selects for editors who tend not to change their CC-Scores is unlikely, as we would then expect this type of user to appear in the population of users who were never nominated to become administrators. If this were the case, then the non-RfA distribution would be a mix of the successful and unsuccessful RfA distributions; instead, the unsuccessful and non-RfA distributions are similar to each other and different from successful RfAs. We run a second test that provides further evidence for the centralizing hypothesis. We construct a matched sample of successful and unsuccessful RfA candidates, matching on the *estimated probability* p_i that editor i's RfA will be successful RfA based on i's pre-RfA behavior. We use the model of Burke and Kraut to estimate the p_is [3]. For each successful RfA j, we find the editor in the unsuccessful RfA set k with p_k closest to p_j (throwing out examples that are not within 1 percentage point). We then compare the population-level behavior of the two sets of editors we are left with. Now that we have controlled for endogenous factors, we expect that the two populations are very similar in intrinsic qualities: the only difference between them should be that the successful ones actually became admins and the unsuccessful ones did not. We again find that the population of successful admins is significantly different, exhibiting more stable behavior than the population of editors who were unsuccessful in their RfAs (see below for details on statistics). This suggests that some aspect of actually being an administrator reduces the propensity for significant behavior changes (incidentally, this makes administrators who do significantly change their editing behavior all the more interesting).

Data and statistics: For the non-RfA users, we use edits before and after a randomly selected edit. The distributions of changes for unsuccessful and non-RfA editors have a significantly higher variance than the distribution for successful RfAs, with the 95% confidence interval on the ratio of the variance of the successful RfA distribution to the variance among non-RfA users being $[0.22, 0.28]$. The 95% confidence interval on the same ratio for unsuccessful and non-RfA users, on the other hand, is $[0.88, 1.11]$ (est. 0.99). Further, the Kolmogorov-Smirnov Test rules out an identical distribution for successful and unsuccessful distributions ($p = 10^{-7}$, $D = 0.109$), and between the successful and non-RfA distributions ($p = 10^{-4}$, $D = 0.086$). We cannot rule out the possibility that the non-RfA and unsuccessful distributions are identical ($p = 0.25$, $D = 0.042$). Closer examination of the tails of the distributions does not show any differences not already explained by the variance. For the matched sample described above, the 95% confidence interval for the ratio of the variances of successful and unsuccessful RfA distributions is [0.32, 0.43]; the conclusions of the KS-tests are unchanged.

5. DISCUSSION

This paper contributes to the literature in two different ways:

first, we introduce new behavioral metrics for quantifying controversial editing on Wikipedia. The measures we introduce can be used (perhaps with domain specific modifications) to triage suspicious behavior for deeper investigation. Second, these measures allow us to contribute to the study of Wikipedia as an evolving social system: along with showing that Wikipedia admins behave in a stable manner, we also identify some intuitively surprising topics of conflict in Wikipedia.

The Controversy Score (C-Score), measures the extent to which an editor is influencing controversial pages. The Clustered Controversy Score (CC-Score) builds on the C-Score, finding single-topic editors of controversial pages. Both metrics are flexible, since they are language- and platform- independent, and can work with different measures of controversy.

We validate the C- and CC-Scores as user-level measures of controversy on a set of blocked users. On a set of administrators, we find several weaknesses of the C-Score: it misses controversial, single-topic editors in the presence of a long tail of related, but less controversial, pages. Further, the C-Score gives undue weight to unfocused vandalism fighting, a common behavior among administrators. The CC-Score solves many of these issues, allowing us to find controversial, single-topic editors, and often finds editors who would not show up ranked highly on just the C-Score measure. The CC-score also enables us to identify interesting Wikipedia-specific phenomena: for example, the substantial levels of controversy associated with some media/entertainment specific pages as well as with some disambiguation pages.

We also show how the CC-Score can be used to analyze behavior changes, both for single editors and in aggregate. We find several instances of dramatic shifts in behavior by administrators upon assuming their responsibilities. At the same time, we show that administrators as a group change their behavior significantly less than any other group of Wikipedians. This consistency appears to be due to the role of administrator itself, rather than being a selection effect.

Future work: While we focus on editors working alone in this paper, an extension of the CC-Score might highlight groups of editors influencing a single, controversial topic; this presents interesting computational and evaluation challenges. Improvements to the CC-Score to better detect manipulation might focus on natural language processing, or on non-local aspects of an editor's behavior. Being platform-independent, the CC-Score is a useful tool for analyzing behavior in general collective wisdom processes; we are interested in applications of the CC-Score to other domains.

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