Edit wars in Wikipedia

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Abstract—We present a new, efficient method for automatically detecting severe conflicts, 'edit wars' in Wikipedia and evaluate this method on six different language Wikipedias. We discuss how the number of edits and reverts deviate in such pages from those following the general workflow, and argue that earlier work has significantly over-estimated the contentiousness of the Wikipedia editing process.

I. INTRODUCTION

The development of Wikipedia (WP) articles is not always a peaceful and collaborative process. This has long been recognized by the WP community, which calls extreme cases of disagreement over the contents of an article an edit war. WP has developed specific guidelines for dealing with edit warring, such as the three revert rule offers a variety of tags to warn about disputes, and even has a humorous listing of the lamest edit wars.

Perhaps the easiest way human readers can detect pages affected by warring (in the English WP, which is the one discussed unless explicitly stated otherwise) is to read through the discussion page (also known as the talk page) associated to each content page looking for telltale signs such as notices requesting cleanup, swearwords and name-calling. When the discussion grows heated, the length of the talk page can exceed the length of the article many times over, so that older discussions must be archived. Another way to detect controversy is to view the history of the page, which can show many war-like acts, in particular editors reverting the work of other editors.

Schneider et al. estimate that among highly edited or highly viewed articles (these notions are strongly correlated, see [2]) about 12% of discussions is devoted to reverts and vandalism, suggesting that the WP development process is highly contentious. In fact, once the great bulk of WP articles is considered, we find the editorial process far more peaceful: as we shall see, around 24k articles, i.e., less than 1% of the 3m articles available in the November 2009 English WP dump, can be called controversial. To sustain such far-reaching conclusions we no longer rely on manual checking, so our primary interest is with the automatic detection of edit wars. Since our interest is with the entire WP process, of which the English WP is just the largest (and most mature) instance, we are primarily interested in language- and culture-independent methods that can be applied uniformly across the range of WPs. Therefore, our methods are based entirely on the history page, as opposed to the more human-readable talk page.

Previous works (including our own) aimed at the automatic detection of editorial conflict and edit wars is summarized in Section II. In Section III we discuss other indicators of controversy and evaluate these in comparison to ours. We offer our conclusions in Section IV.

II. AUTOMATIC CONFLICT DETECTION

Conflicts in WP were studied already both on the article and on the user level. Kittur et al. computed article controversy from different page metrics (number of reverts, number of revisions etc.), Vuong et al. counted the number of deleted words between users and used their “Mutual Reinforcement Principle” to measure how controversial a given article is. Both teams counted how many times dispute tags appeared in the history of an article, and used this as ground truth. While this is an excellent test in one direction (certainly recognition of controversy by the participants is as good as the same recognition coming from an outsider), it is too narrow, as there can be quite significant wars that the community is unaware of or at least do not tag, as, e.g., in the articles on Gdansk or Euthanasia. Note that by applying more lax criteria (i.e. not requiring the presence of overt conflict tags) our method will, if anything, overestimate the extent of controversy, strengthening our conclusion that there is much less conflict in WP than appears from sampling highly edited/viewed pages.

There are several papers which try to measure the negative links between WP editors in a given article and, based on this, attempt to classify editors into groups. The main idea of the method used by Kittur et al. is to count how many times an editor pair reverted each other. The more two editors reverted each other, the larger the conflict between them. As we shall see shortly, reverts are indeed central to the assessment of controversy, but one needs to take into account not just the number of (presumably hostile) interactions, but also the seniority of the participants. Brandes et al. assumed that users who do not agree with each other react very fast to edits by the others. The reciprocal value of the time elapsed between two consecutive edits increases the controversy between the two authors. In a more recent paper Brandes counted the
number of deleted words between editors and used this as a measure of controversy. West et al. and also Adler et al. have developed vandalism detection methods based on temporal patterns of edits [8, 9]. In both works the main assumption is that offensive edits are reverted much faster than normal edits, therefore by considering the time interval between an arbitrary edit and its subsequent reverts, one can classify vandalized versions with high precision.

Our own work (for a preliminary report, see [10]) was seeded by a manual sample of 40 articles, 20 selected for high controversiality, and 20 for low. Table I summarizes the number of reverts as detected in the text and in the comments (most reverts are detected by both methods).

**TABLE I**

| Article title | Number of reverts detected |
|---------------|-----------------------------|
| Global warming | 4103 |
| Homosexuality | 2375 |
| Abortion | 1948 |
| Elvis Presley | 1494 |
| Nuclear power | 1396 |
| Niccolao Copernicus | 1297 |
| Tiger | 1071 |
| Euthanasia | 1036 |
| Alzheimer’s disease | 937 |
| Gun politics | 870 |
| Sherlock Holmes | 836 |
| Arab-Israeli conflict | 689 |
| Israel and the apartheid analogy | 659 |
| Liancourt Rocks | 652 |
| Schizophrenia | 642 |
| Gaza war | 516 |
| 1948 Arab-Israeli war | 431 |
| Pumpkin | 416 |
| Gdansk | 380 |
| SQL | 318 |

| Article title | Number of reverts detected |
|---------------|-----------------------------|
| Password | 162 |
| Henry Cavendish | 116 |
| Pension | 109 |
| Mexican drug war | 81 |
| Hungarians in Romania | 74 |
| Markov chain | 70 |
| Mentha | 70 |
| Foucault pendulum | 47 |
| Indian cobra | 40 |
| Harmonium | 32 |
| Infrared photography | 30 |
| Bohrium | 29 |
| Anyos Jedlik | 24 |
| Hungarian forint | 11 |
| Hendrik Lorentz | 10 |
| 1980s oil glut | 9 |
| Deutsches Museum | 7 |
| Ara (genus) | 4 |
| Schlenk flask | 0 |

Given the number and distribution of false positives and negatives (typeset in italics) it is clear from Table I that the raw revert statistics do not yield a clear cutoff-point we could use to distinguish controversial from non-controversial articles. Rather than building a complex but arbitrary formula that includes different factors that are expected to correlate with controversy, our goal is to base the decision on very few parameters – ideally, just one.

Let \( \ldots, i - 1, i, i + 1, \ldots, j - 1, j, j + 1, \ldots \) be stages in the history of an article. If the text of revision \( j \) coincides with the text of revision \( i - 1 \), we considered this a revert between the editor of revision \( j \) and \( i \) respectively. We are interested in disputes where editors have different opinions about the topic, and do not reach consensus easily.

Let us denote by \( N_i \) the total number of edits in the given article of that user who edited the revision \( i \). We characterize reverts by pairs \((N_i^d, N_j^r)\), where \( r \) denotes the editor who makes the revert, and \( d \) refers to the reverted editor (self-reverts are excluded). Fig 1 represents the revert map of the non-controversial Benjamin Franklin and the highly controversial Israel and the apartheid analogy articles. Each mark corresponds to one or more reverts. The coordinates of the marks are the total number of edits of the reverter \((N^r)\) and the reverted editor \((N^d)\). Clearly, the disputed article contains more reverts between editors having large edit numbers than the uncontroversial article.

![Fig. 1. Revert maps of the articles Benjamin Franklin (left) and Israel and the apartheid analogy (right). \( N^r \) and \( N^d \) are the total number of edits of the reverter and reverted editor respectively. The size of the mark is proportional to the number of reverts between them.](image1.png)

![Fig. 2. Maps of mutual reverts in the same articles as in Fig. 1.](image2.png)

The revert maps already distinguish disputed and non-disputed articles, and we can improve the results by considering only the cases, in which two editors revert each other mutually, hereafter called *mutual* reverts. This causes little change in disputed articles (compare the right panels of Fig 1 to that of Fig 2), but has great impact on non-disputed articles (compare left panels).
Based on the rank (total edit number within an article) of editors, two main revert types can be distinguished: when one or both of the editors have few edits to their credit (these are typically reverts of vandalism since vandals do not get or both of the editors have few edits to their credit (these editors, two main revert types can be distinguished: when one

sures, including the presence of tags marking controversiality

cluded that its overall performance is superior to other mea-

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TABLE III

| WP | #e | #r | #mt | Mr | M1 | TC | M |
|----|----|----|-----|----|----|----|--|
| ca | 14 | 18 | 26  | 25 | 27 | 27 | 28|
| en | 27 | 29 | 26  | 28 | 30 | 28 | 28|
| hu | 4  | 27 | 28  | 23 | 29 | 24 | 30|
| fa | 24 | 28 | 26  | 29 | 29 | 25 | 28|
| es | 23 | 26 | 29  | 27 | 28 | 28 | 29|
| %av| 61 | 85 | 92  | 87 | 94 | 89 | 95|

On the whole, articles with low tag count but high M appear to be quite controversial, even if the participants themselves fail to tag the article for controversy. The opposite situation, with low M and high TC, is found very rarely. Besides an inherently lower precision and recall, there are some mechanical reasons why counting controversial tags is not a perfect method to detect disputes. There are many dispute-related tags and one has to decide which tags to count on a per-language basis. Page [11] contains all disputed tags.
but some may indicate more serious conflict than others (for example compare {{Unreferenced}} to {{Disputed}}).

The limitations of the earlier proposals such as [3] and [4] are evident if we check the results. For example, [4] concluded that in the Podcast article “a significant amount of dispute occurred between the two pairs of users: (a) user 210.213.171.25 and user Jamadagni; and (b) user 68.121.146.76 and user Yamamoto Ichiro”. A closer look at the article reveals that user 210.213.171.25 edited the given article only once, and his edit was a vandalism, because he multiplied several time the text of the article, creating a revision which was 20 times larger than the previous one. Jamadagni simply reverted, generating this way a large number of deleted words between them. Real, recurrent disputes cannot produce this large amount of deleted words, therefore they remain hidden. (This is not an extreme example, user 68.121.146.76 is another vandal, who edited the article only once.)

IV. CONCLUSION, FUTURE DIRECTIONS

We proposed a new way to measure how disputed a WP article is. We did this because existing models have drawbacks, and only a small fraction of WP articles were analyzed with them. We analyzed the whole WP for different language versions, and ranked articles according to their controversy level. Altogether, the proposed measure $M$ fares considerably better than earlier proposals both for precision and recall, though this fact would not be evident to the observer restricted to the top 30 articles of the English WP. For example, in Romanian even TC fails rather spectacularly. Based on the results obtained by our classifier, we conclude that in most cases, the process of development of the articles is considerably peaceful and the number of conflict cases have been overestimated in previous works, compared to our estimation of less than 1% of articles to be a candidate for a serious conflict. Besides being a robust language- and culture-independent classifier, our method also yields a numerical ranking, which agrees well with human judgment.

While our method does well in separating out edit wars from vandalism at the high end, much work remains to be done for lower $M$. Researchers interested in a better controversies measure may go back to the other indicators of controversiality and mix these into the measure: the largest limiting factor is the number of manually truthed examples one is willing to create for training and testing, but if resources are pooled across teams or the judgement task could be automated (e.g. by the Mechanical Turk) this limitation can be overcome.

Our future goals include detection of pure (non-war-like) vandalism, a task made all the more important by the high degree of vandalism we see. Another goal is the prediction of impending edit wars by monitoring the dynamics of $M$ – once a reasonable predictor is provided it will be possible to tag pages for impending conflict by robots.

ACKNOWLEDGMENT

This work was supported by the EU’s 7th Framework Programs FET-Open within ICTeCollective project no. 238597. Kornai also acknowledges support from OTKA grants #77476 (Algebra and algorithms) and #82333 (Semantic language technologies). Special thanks to Santo Fortunato for discussions and his help with data at early stages of this work.

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