Assigning Trust to Wikipedia Content*

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Abstract

The Wikipedia is a collaborative encyclopedia: anyone can contribute to its articles simply by clicking on an "edit" button. The open nature of the Wikipedia has been key to its success, but has also created a challenge: how can readers develop an informed opinion on its reliability? We propose a system that computes quantitative values of trust for the text in Wikipedia articles; these trust values provide an indication of text reliability.

The system uses as input the revision history of each article, as well as information about the *reputation* of the contributing authors, as provided by a reputation system. The trust of a word in an article is computed on the basis of the reputation of the original author of the word, as well as the reputation of all authors who edited the text within proximity of the word. The algorithm computes word trust values that vary smoothly across the text; the trust values can be visualized using varying text-background colors. The algorithm ensures that all changes to an article text are reflected in the trust values, preventing surreptitious content changes.

We have implemented the proposed system, and we have used it to compute and display the trust of the text of thousands of articles of the English Wikipedia. To validate our trust-computation algorithms, we show that text labeled as low-trust has a significantly higher probability of being edited in the future than text labeled as high-trust. Anecdotal evidence seems to corroborate this validation: in practice, visitors find the trust information valuable.

1 Introduction

The Wikipedia is one of the most successful collaborative sites on the Web. This on-line encyclopedia, available in multiple languages, has grown entirely due to user-contributed content, with contributors ranging from casual visitors to dedicated, volunteer, editors. This user-generated growth is the basis of Wikipedia's remarkable breadth: as of October, 2007, the Wikipedia consisted of over two million articles, compared with approximately 120,000 for the online Encyclopedia Britannica [33]. On the other hand, the open process that gives rise to Wikipedia content makes it difficult for visitors to form an idea of the reliability of the content. Wikipedia articles are constantly changing, and the contributors range from domain experts, to vandals, to dedicated editors, to superficial contributors not fully aware of the quality standards the Wikipedia aspires to attain. Wikipedia visitors are presented with the latest version of each article they visit: this latest version does not offer them any simple insight into how the article content has evolved into its most current form, nor does it offer a measure of how much the content can be relied upon. These considerations generated interest in algorithmic systems for

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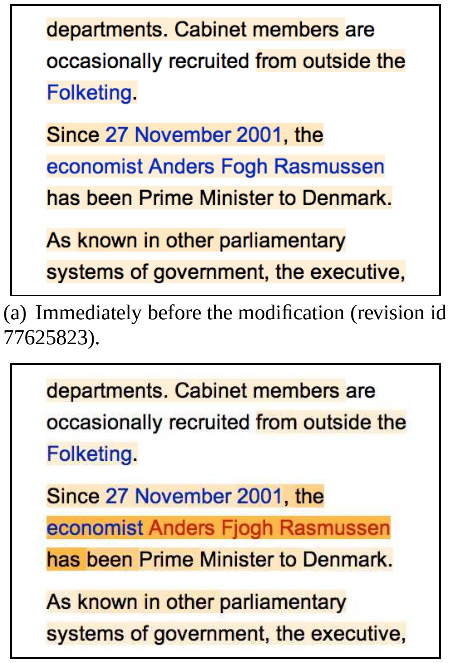

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(b) Immediately after the modification (revision id 77692452).

Figure 1: Trust coloring resulting from an attempt to modify the spelling of the Danish Prime Minister's last name, from Fogh, to Fjogh (in Danish, a fjog is a fool). The text background is a shade of orange that is the darker, the lower the trust of the text. The sequence consists of two consecutive revisions. Notice how the trust coloring highlights the information that has not yet been sufficiently reviewed. Subtle changes such as the above can be hard for Wikipedia visitors to spot without the help of a trust coloring.

estimating the trust of Wikipedia content [21, 35].

We introduce a trust system for Wikipedia content that assigns trust at word level, enabling readers to easily and accurately spot new, unchecked content, as well as word substitutions, text rearrangements and deletions, and other forms of content modification. Our emphasis on word-level trust is due to the fashion in which content evolves on the Wikipedia. Often, as articles evolve, some sections take shape first, and become stable, and thus trustworthy, while other sections are still undergoing constant change. Once an article is mature, each constructive (non-vandalistic) edit usually affects only a small portion of the article text. Our intent consists in providing guidance to Wikipedia visitors over which portions of an article can be relied upon, and which others instead require closer scrutiny. Thus, we seek *local* trust information for article text. This contrasts with approaches that assign a single, *global* value of trust or quality for an entire article [18, 7, 36, 23]. Such a global trust value is useful in many applications, including applications where *selecting* articles is important. We instead assume that a reader is interested in a given article, and we tackle the goal of providing an estimate of how much the different assertions in the article can be trusted. Our system displays the trust values of each portion of text by coloring its background. An example of coloring produced by our system is given in Figure 1; the tampering with the prime minister's last name is clearly indicated by the trust values.

A novel feature of our trust system is that it is resistant to tampering. Text that is deleted by vandalism, and then re-inserted, conserves its original trust, so that malicious users cannot lower the trust of text simply by deleting and re-inserting it. More importantly, users cannot tamper with the system and cause text of their choice to gain extra trust. Another novel feature of the proposed trust system is that it relies on content analysis only: no additional information about users is required. Past systems relied on a classification of users according to their Wikipedia role [21, 35], and as a consequence, were applicable only to wikis that developed such a stratified classification of contributors; our methods, in contrast, are applicable to any wiki.

Finally, we introduce several quantitative measures of the quality of a trust labeling. These measures are fully general, and they can be applied to any trust labeling of versioned information; they are not specific to the particular way in which we compute the trust. We have implemented the proposed trust system and we provide comprehensive evaluation data on the performance of the trust system over the English Wikipedia, indicating that the trust values we compute are good predictors for the future longevity and stability of Wikipedia information.

1.1 The Trust Assignment Algorithm

The trust system relies on a simple principle: the trust of text should depend on the reliability of the author, and on the reliability of the people who subsequently revised, checked, and edited the text [21, 35]. As a measure of author and revisor quality, we take the *author reputation* computed by an author reputation system [15, 25, 5, 13, 1]. The precise nature of the reputation system is not important; all we need to assume is that:

- author reputation has a strong correlation with the quality of the author's contributions;
- gaining reputation requires effort on the author's part, and high reputation cannot be acquired in a short time span.

As our results will show, the use of a reputation system yields two benefits:

- The information on author quality leads to improved trust quality (see Section 5.1).

- The effort required to gain reputation enables us to make the trust resistant to tampering, including to sock-puppet attacks (see Section 2.4).

The trust system computes the trust of the text of the revisions $v_1, v_2, v_3, \ldots$ of a wiki article by analyzing how each revision is obtained from the previous one. When an author A edits revision v_k, obtaining revision v_{k+1}, we compare the text of v_k and v_{k+1}, tracking the blocks of text that have been inserted, deleted, and copied.

Text that is new in v_{k+1} is given a trust proportional to A's reputation: the rationale is that authors of high reputation are likely to provide good quality, accurate contributions. We choose the proportionality constant so that even text by top-reputation authors does not initially have full trust. Our aim is to ensure that *high trust requires consensus:* text can gain top trust only by being revised by multiple authors.

The text that used to be present in v_k, but has been deleted, is tracked as "dead text", so that if it is reinserted in a later revision v_{k+m}, for $m > 1$, it can be assigned the trust it had in v_k. Tracking deleted text helps to ensure that vandalism has no lasting effect, and is not gratifying to the vandals. If we did not track deleted text, vandals who deleted all or portions of an article would succeed in destroying the trust information of the text, thereby affecting lasting damage to the article. As a side benefit, tracking deleted text also enables us to accurately attribute the text to its original author.

If author A rearranged the order of blocks of text in producing revision v_{k+1} from v_k, we assign the end-points of the rearranged blocks the same trust value we assign to new text. Indeed, the meaning of the text may have changed due to the cut-and-paste, and it is no more reliable than other text inserted by author A. The trust of the block interior is inherited from the trust of the corresponding text in v_k. A consequence of this rule is that when text is deleted, the margings of the "wound" where the text has been cut are highlighted with low trust, as they correspond to end-points of rearranged text blocks. Thus, our system makes it hard to surreptitiously tamper with the content of Wikipedia articles: every change, including text rearrangements and deletions, leaves a low-trust mark that is prominently displayed via the trust coloring.

Once all the text of revision v_{k+1} is assigned a preliminary value of trust as described above, we perform one additional step, in which we may raise the trust of the text to account for the fact that it has been reviewed by author A. The idea is that author A, by leaving text unchanged from v_k to v_{k+1}, has given an implicit vote of confidence in the text. Thus, we raise the trust of the text in proportion to A's reputation, and in proportion to the attention that A is likely to have paid to each portion of text. The algorithm assumes that the attention level of A, while performing the edit from v_k to v_{k+1}, was higher for the portions of text affected by the edit, and lower for other portions. Text of v_{k+1} that has trust lower than A's reputation receives an increment in trust which depends on A's reputation and attention level. The trust increment is chosen so that several revisions are required for text to gather high trust: a single revision is not sufficient. If text has trust higher than A's reputation, the trust is not modified during this revision step: authors can cause the trust of text to raise only up to their own reputation. To ensure that a single author cannot cause the trust of an article to raise more than due by performing repeated small edits, we keep track, for each word, of the list of the last n authors who raised the word's trust. An author can cause a word to raise in trust only if she does not appear in this list. This ensures that text can only raise in trust if revised by multiple authors, preventing authors from single-handedly raising the trust of portions of text of their choice. We show (in Section 2.4) that this also ensures robustness against direct and sock-puppet attacks.

The trust system contains many parameters, such as the proportionality constant for trust inheritance, the author list length, and more. We estimated the values of the parameters via an optimization process, aimed at maximizing the quantitative measures of trust quality that will be described in Section 1.2.

We would like to point out some techniques and factors that we have chosen *not* to consider in computing text trust. We chose not to perform semantic analysis of the sentences affected by the edits. Undoubtedly, such an analysis would yield additional information. On the other hand, our methods have the advantage of simplicity, and they are suited to most languages with no adaptation required (as long as the text can be split into individual words); thus, we believe it is of interest to characterize how well trust can be associated with text without requiring semantic analysis. We also chose to consider all words equally, disregarding for instance the distinction between common words, and rarer ones. The meaning of a sentence can be drastically affected by changing common words, such as an "and" into a "not", and we did not wish to build into the algorithm preconceived ideas of what changes were important. Finally, we chose to consider text as a sequence of words, without attempting to separate it into individual sentences. Assigning trust to individual words, rather than to whole sentences, has the side-effect of highlighting, in an intuitive way, which portions of text have been affected by recent edits, as illustrated in Figure 1. We do not doubt that our results can be improved by considering additional factors, but we opted to evaluate a simpler, more general approach first.

A simpler idea than computing trust according to author reputation consists in using some notion of text "age", where age is measured either in time for which text has been present, or in the number of revisions for which text has been present. We show in Section 5.1 that using the revision-age of text to compute trust makes the trust values very susceptible to attacks, and yields inferior results. Using time as a measure of age is also problematic, due to the difference in edit rates across articles. Furthermore, while trust based on text age is conceptually simpler, the conceptual simplification does not translate in a large software simplification, as we argue in Section 5.2.

1.2 Trust Quality Measures

To evaluate the quality of our trust labeling, one idea is to measure the correlation between the trust values of the labeling, and the truth of the information encoded in the text, as assessed by human subjects. However, "truth" is a poorly-defined notion: indeed, accuracy investigations of Wikipedias and other encyclopedias have confined themselves to articles on science, where truth — or rather, scientific consensus — is easier to assess [8]. Furthermore, any human assessment of "truth" in Wikipedia articles would be very labor intensive. For these reasons, we introduce four data-driven, quantitative measures of the quality of a trust labeling, following the idea that *trust should be a predictor for text stability* [35].

The four measures we introduce quantify the ability of low-trust to be a predictor for text deletions, and thus, of high-trust as a predictor of future text longevity. The intuitive justification behind the measures is that low-trust text should be more likely to be deleted than general text, as users seek to correct or improve it, thereby deleting portions of it. Let the possible range of trust values be the interval $[0, T_{\max}]$. The first two measures consider the precision and recall of low-trust with respect to immediate deletions:

- *Recall of deletions.* For $\rho \in [0, T_{\max}]$, the *ρ-recall of deletions* is the percentage of deleted text that had trust lower than ρ in the revision preceding its deletion.

- *Precision of deletions.* For $\rho \in [0, T_{\max}]$, the *ρ-precision of deletions* is the percentage of text with trust lower than ρ that is deleted in the immediately subsequent revision.

The third measure consider the distribution of trust values for general text, as compared to text that is deleted. In a good trust labeling, deleted text should be on average of low trust. Furthermore, we argue that general text should have as high trust as possible on average: low-trust should be used to warn readers of unreliable information, and the warning, if over-used, loses effectiveness:

- *Trust of average vs. deleted text.* We consider the average and median trust of all the text, compared with the average and median trust that deleted text possesses immediately prior to deletion.

In the previous quality measures, trust is evaluated with respect to its ability to predict deletions that occur in the very next revision. Our last quality measure quantifies the abilty of trust to predict the entire future lifespan of text.

- *Trust as a predictor of lifespan.* We select words uniformly at random, and we consider the statistical correlation between the trust of the word at the moment of sampling, and the future lifespan of the word. For $\rho \in [0, T_{\max}]$, the *ρ-trust average lifespan* of text is the average number of future revisions in which a word of trust ρ at sampling appears.

We remark that this is a proper test, since the trust at the time of sampling depends only on the history of the word prior to sampling.

1.3 Implementation and Evaluation

We have implemented the trust system using, as a source of author reputation, the *content-driven* reputation system of [1]. The code of the reputation and trust systems has been made available in open-source format [29]; the code can be readily applied to wikis other than the Wikipedia.

The trust system has been used to process all the text of the English Wikipedia, as of February 2007. The resulting trust assignments can be viewed in a live demo, in which text is displayed with a background color that depends on its trust: white background for fully trusted text, and shades of orange that are the darker, the lower the text trust [29]. The demo provides information on both text trust and text provenance: when visitors click on a word in an article, they are redirected to the version of the article where the word was first introduced. The trust and provenance information complement each other: visitors are made aware of the less trusted portions of text by the coloring, and can then investigate the origin of such text via the text origin redirection.

We present in Section 5 the detailed evaluation results for our trust metric; the results can be summarized as follows:

- *Recall of deletions.* We show that text in the lowest 50% of trust values constitutes only 3.4% of the text of articles, yet corresponds to 66% of the text that is deleted from one version to the next.

- *Precision of deletions.* We show that text that is in the bottom half of trust values has a probability of 33% of being deleted in the very next version, in contrast with the 1.9% probability for general text. The deletion probability raises to 62% for text in the bottom 20% of trust values.

- *Trust of average vs. deleted text.* We show that 90% of the text overall had trust at least 76%, while the average trust for deleted text was 33%.

- *Trust as a predictor of lifespan.* We show that words with the highest trust have an expected future lifespan that is 4.5 times longer than words with no trust.

The above results were obtained by analyzing 1,000 articles selected randomly from the Wikipedia articles with at least

200 revisions. Considering articles with at least 200 revisions ensures that the measures on text stability are accurate. Taken together, these results indicate that the trust labeling we compute is a good predictor of future text stability.

The current implementation of the trust system relies on *batch* processing: the code examines all the content, and computes the trust value of each word of each article revision. We are currently working on an *on-line* implementation, in which new revisions of Wikipedia articles are colored according to trust in real-time, as they are created by users. No change in the basic trust (or reputation) algorithms is required for such an implementation; only the way the algorithms are applied to revisions changes.

1.4 Related Work

The problem of the reliability of Wikipedia content has often emerged both in the press (see, e.g., [27, 12]) and in scientific journals [8]. The idea of assigning trust to specific sections of text of Wikipedia articles as a guide to readers has been previously proposed in [21, 4, 35], as well as in white papers [14] and blogs [20]; these papers also contain the idea of using text background color to visualize trust values.

The work most closely related to ours is [35], where the trust of a piece of text is computed from the Wikipedia roles (anonymous, registered user, or editor) of the original author, and of the authors who subsequently revised the article. The Wikipedia roles of authors are thus used in lieu of author reputation; as a consequence, the algorithm can only be applied to wikis where authors are organized in a well-defined hierarchy. Text analysis is performed at the granularity level of sentences; all sentences introduced in the same revision form a *fragment*, and share the same trust. A change anywhere in a sentence causes the whole sentence to be considered new, and the position of the change in the sentence is not flagged via the trust labeling. The cut-and-paste edges of text deletions and reorderings are also not flagged via the trust labeling. Furthermore, deleted text is not tracked: when text is deleted, and then re-inserted, it is counted as new. Among other things, this creates an incentive to vandalism: blanking an article suffices to reset its entire trust assignment. To validate the trust assignment, [35] computes the correlation between the trust of a fragment, and the probability that the fragment appears in the most recent version of the article. We refine this criterion into one of our evaluation criteria, namely, the predictive power of trust with respect to word longevity.

In [21], the trust of authors and fragments is computed on the basis of the author-to-fragment and fragment-of-article graphs, together with the *link ratio* of article titles. The *link ratio* is the ratio of the number of times an article title appears as a link in other articles, and the number of times the title appears as normal text. The work provides trust values for some articles, but no comprehensive evaluation.

The white paper [14] focuses on the user interface aspects of displaying information related to trust and author contributions; we hope to include some of the suggestions in future versions of our system. Related work that relies on an analysis of revision information to infer trust has been performed in the context of software, where logs are mined in order to find revision patterns that point to possible software defects and weak points (see, e.g., [19]).

Other studies have focused on trust as article-level, rather than word-level, information. These studies can be used to answer the question of whether an article is of good quality, or reliable overall, but cannot be used to locate in an article which portions of text deserve the most careful scrutiny, as our approach can. In [36], which inspired [35], the revision history of a Wikipedia article is used to compute a trust value for the entire article. In [7, 23], metrics derived via natural language processing are used to classify articles according to their quality. In [18], the number of edits and unique editors are used to estimate article quality. The use of revert times for quality estimation has been proposed in [30], where a visualization of the Wikipedia editing process is presented; an approach based on edit frequency and dynamics is discussed in [34]. There is a fast-growing body of literature reporting on statistical studies of the evolution of Wikipedia content, including [30, 31, 24]; we refer to [24] for an insightful overview of this line of work.

The notion of trust has been very widely studied in more general contexts (see, e.g., [2, 10]), as well as in e-commerce and social networks (see e.g. [15, 25, 5, 13, 11, 9]); these notions of trust however are generally based on user-to-user feedback, rather than on an algorithmic analysis of content evolution.

2 Text Trust Algorithms

We compute the trust of Wikipedia text on the basis of an algorithmic analysis of how the content of Wikipedia articles evolve across revisions. We assume that, in addition to the text of all article revisions, we have access to a reputation system that, at every point in time, can give us a value of reputation for each author; we assume that reputations take values in a fixed interval $[0, T_{\max}]$, for some $T_{\max} > 0$. Our goal consists in associating a value of trust in the interval $[0, T_{\max}]$ to every word of every article revision.

We present our algorithm for trust assignment in three steps. First, we will illustrate the basic idea via a simplified algorithm that does not cope with reversions, nor in general, with the situation when text is deleted, and later re-inserted. Next, we present an improved algorithm for assigning trust to Wikipedia content that deals with removed-and-reinserted text, and that also contains a tuned model of user attention during the process of article revision. Finally, we discuss the modifications to the algorithm that we introduced to make the trust system robust to tampering.

2.1 Notation

We denote the sequence of revisions of a Wikipedia article by $v_0, v_1, v_2, \ldots$. Version v_0 is empty, and version v_i, for $i > 0$, is obtained by author a_i performing an edit $e_i = v_{i-1} \rightsquigarrow v_i$. When editing a versioned document, authors often save intermediate results, thus performing multiple consecutive edits. Before processing the versions, we filter them, keeping only the last of consecutive versions by the same author; we assume thus that for $1 \leq i < n$ we have $a_i \neq a_{i+1}$. Every version v_i, for $0 \leq i \leq n$, consists of a sequence $[w^i_1, \ldots, w^i_{m_i}]$ of *words,* where m_i is the number of words of v_i; we have $m_0 = 0$. Our system works at the level of the Mediawiki markup language in which authors write article content, rather than at the level of the HTML produced by the wiki engine; a *word* is a whitespace-delimited alphanumerical string in the Mediawiki markup language.

2.2 A simplified text-trust algorithm

Our trust algorithms will assign a trust value in the interval $[0, T_{\max}]$ for each word of each article revision. Given an edit $e_i = v_{i-1} \rightsquigarrow v_i$, a trust value $t_1, t_2, \ldots, t_{m_{i-1}}$ for each word of v_{i-1}, and a value $r \in [0, T_{\max}]$ for the reputation of the author a_i of the revision, the algorithm computes trust values $\hat{t}_1, \hat{t}_2, \ldots, \hat{t}_{m_i}$ for all words of v_i. The algorithm first computes an *edit list* L_i detailing how v_i is obtained from v_{i-1} [28]. The edit list L_i consists of one or more of the following elements:

- $I(j,n)$: n words are inserted at position j of v_i (i.e., words of indices from j to $j+n-1$ are new in v_i);
- $R(j,n)$: n words are deleted at position j of v_{i-1};
- $M(j,j',n)$: n words are moved from position j in v_{i-1} to position j' in v_i (it may be $j = j'$).

Each word in v_i is part of exactly one of the above $I(\cdot)$ or $M(\cdot)$ elements, and the algorithm to generate edit lists tries to maximize text block matches [1]. The trust computation algorithm uses the following constants:

- $0 \leq c_l < 1$ is the *trust inheritance constant:* it specifies how much trust should a word inherit from the reputation of its author.
- $0 \leq c_r < 1$ is the *revision constant:* it specifies how much trust does the author reputation confer to the text of the article.
- $c_e > 0$ is the *edge effect constant:* when blocks of text are displaced, this constant specifies how far into the blocks is the trust of the text affected by the move.

The values of these constants are obtained via optimization techniques that will be described later. We first compute preliminary trust values $t'_0, t'_1, \ldots, t'_{m_i}$ by considering all elements in the edit list L_i:

1. *Insertions.* If $I(j,n) \in L_i$, then $t'_k := c_l \cdot r$ for all $j \leq k < j+n$: thus, inserted text is assigned a trust value equal to the reputation of the author inserting it, multiplied by the trust inheritance constant.
2. *Block moves.* If $M(j,j',n) \in L_i$, then for all $0 \leq k < n$, k is the distance of the k-th word in the block from the beginning of the block, and $\bar{k} = n - 1 - k$ is the distance from the end of the block. We apply an *edge effect,* whereby the text at the block boundary acquires the same trust as new text; this edge effect weakens exponentially towards the interior of the block. The edge effect is not applied to block move boundaries that remain at the beginning or end of the article. Precisely:

   (a) If $j \neq 0$ or $j' \neq 0$ then the left endpoint of the block has changed context, and we let:

   $$t''_{j'+k} = t_{j+k} + (c_l \cdot r - t_{j+k}) \cdot e^{-c_e k}$$

   Otherwise, if $j = 0$ and $j' = 0$, we let $t''_{j'+k} = t_{j+k}$.

   (b) If $j + n \neq m_{i-1}$ or $j' + n \neq m_i$, then the right endpoint has changed context, and we let:

   $$t'_{j'+k} = t''_{j'+k} + (c_l \cdot r - t''_{j'+k}) \cdot e^{-c_e \bar{k}}$$

   Otherwise, if $j + n = m_{i-1}$ and $j' + n = m_i$, we let $t'_{j'+k} = t''_{j'+k}$.

If $R(j,n) \in L_i$, then the text is deleted, and there is no trust assignment to be made (the edge effect of adjacent blocks to $R(j,n)$ will take care of flagging the deletion in the new version). Once all elements of the edit list L_i have been processed, we have preliminary trust values $t'_1, t'_2, \ldots, t'_{m_i}$ which take into account of insertions, block moves, and edge effects. The final trust values $\hat{t}_0, \hat{t}_1, \ldots, \hat{t}_{m_i}$ of the words of v_i are then computed by accounting for the fact that the author a_i lends some of her reputation r to the revision v_i she just performed. For $0 \leq k < m_i$, we let:

$$\hat{t}_k = \begin{cases} t'_k & \text{if } t'_k \geq r \\ t'_k + (r - t'_k) \cdot c_r & \text{if } t'_k < r \end{cases} \quad (1)$$

The trust update process is illustrated in Figure 2. The trust labeling computed by the algorithm is such that high trust requires consensus: only text that survives scrutiny by multiple authors can gain high trust. The trust labeling also provides a warning when text is deleted or reordered. However, this simplified algorithm, however, has a fatal flaw: it does not cope with text that is deleted in a revision, only to be reinserted in a later one. Deletion and reinsertion is a common

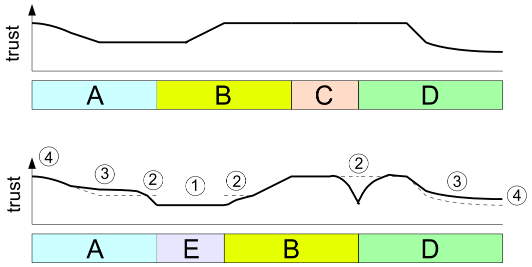

Figure 2: Update process for text trust. The text is shown before (top) and after (bottom) an edit, together with its trust. In the bottom figure, the new values of trust (continuous line) are obtained from the inherited values of trust (dashed line) as follows: 1: Trust value for newly inserted text (E). 2: Edge effect: the text at the edge of blocks has the same trust as newly inserted text. 3: Revision effect: old text may increase in trust, if the author reputation is higher than the old text trust. 4: The edge effect is applied at the beginning and end of the article only if text changes there (which is not the case here).

phenomenon in the evolution of Wikipedia articles: it occurs in many disputes about article content, and even more devastatingly, it occurs when visitors deface articles by removing part or all of their text. If this algorithm were applied to the Wikipedia, a vandal would simply need to delete, and then re-insert, existing text in order to reset its trust to zero. Thus, it would be extremely easy for vandals to destroy trust information and deface the coloring provided by the trust system.

2.3 An improved text-trust algorithm

We describe now an improved text-trust algorithm, which keeps track not only of the trust of the text present in an article, but also of the trust of the text that used to be present, but that has subsequently been deleted. The algorithm also models the attention focus of the author performing an edit, raising by a larger amount the trust of the text that is most likely to have been read by the author in the course of the edit.

2.3.1 Tracking deleted text.

We track deleted text by representing each article version v_i, for $1 \leq i \leq n$, as a non-empty list $C_i = [c_0^i, c_1^i, \ldots, c_{h_i}^i]$ of *chunks*, where each chunk c_k^i, for $0 \leq k \leq h_i$, is a sequence of words. The *live* chunk c_0^i corresponds to the words that are present in v_i; the *dead* chunks c_1^i, …, $c_{h_i}^i$, if present, correspond to contiguous portions of text that used to be present in some prior version $v_0, \ldots, v_{i-1}$ of the article, but have been deleted. The chunks C_i are computed from the chunks $C_{i-1} = [c_0^{i-1}, c_1^{i-1}, \ldots, c_{h_{i-1}}^{i-1}]$ for v_{i-1} as described in [1]. Specifically, we match the text of v_i with the text of all the chunks in C_{i-1}, looking for the longest possible matches of contiguous sequences of words. We break ties in favor of matches between v_i and the text c_0^{i-1} that was present in v_{i-1}, thus preferring matches between v_i and the live text in v_{i-1}, to matches between v_i and the text $c_1^{i-1}, \ldots, c_{h_{i-1}}^{i-1}$ that was present before v_{i-1} but is "dead" in v_{i-1}. Furthermore, we allow the text in C_{i-1} to be matched multiple times, modeling the fact that an author can replicate existing text; the text in v_i can be matched at most once. The portions of unmatched text in C_{i-1} go on to form the new dead chunks $[c_1^{i-1}, \ldots, c_{h_{i-1}}^{i-1}]$ for v_i. In this matching process, lower bounds on the length of acceptable matches ensure that common sequence of words (such as "the" or "in fact") appearing in new contexts are not considered as copied or re-introduced text.

We update the trust of deleted and reinserted text as follows.

- For text that is moved from the live chunk c_0^{i-1} to some dead chunk $c_{h'}^i$, $h' > 0$, we multiply the trust of the text by e^{-rc_k}. The idea is that when text is deleted, its trust is decreased in proportion to the reputation r of the author deleting the text. In particular, text does not lose trust when deleted by anonymous users or novices ($r = 0$). This ensures that when vandals remove all text of an article, once the text is re-inserted it has the same trust as before the vandalism occurred. In our implementation, we have taken $c_k = (\log 2)/T_{\max}$, so that the trust of a word is halved when deleted by an author of maximum reputation.

- For text that is moved from a dead chunk c_h^{i-1}, $h > 0$, to another dead chunk $c_{h'}^i$, $h' > 0$, we simply copy the trust.

- For text that is moved from a dead chunk c_h^{i-1}, $h > 0$, to the live chunk c_0^i, we update the trust in a manner completely equivalent to the one used for block moves $M(j, j', n)$ in the previous section, applying the edge effect to both text endpoints.

2.3.2 Modeling author attention.

In equation (1) of the previous algorithm, we increase the trust of the text uniformly — this assumes that the author of the revision pays equal attention to the entire text being revised. This assumption is unlikely to be correct, as authors are more likely to pay greater attention to text that is closer to their edits; raising the trust of all the text in the article may impart too much trust to text that has not been the focus of author attention. We decided therefore to experiment with a variation of the algorithm that models author attention in a rudimentary fashion.

When parsing the text of the revision v_i, we split it into paragraphs, where section titles, items in a bulleted or numbered list, image captions, and table cell entries also count as "paragraphs". Our algorithm then follows the simple idea that authors are likely to pay more attention to the text in the same paragraph as the edits they are performing. To this end, we mark as *modified* all paragraphs where (a) either new text has been inserted (corresponding to an I element in the edit list), or (b) the paragraph contains the endpoint of a block move (elements M in the edit list) to which the edge effect applies. For modified paragraphs we apply, after (1), the following update:

$$\hat{t}_k := \begin{cases} \hat{t}_k & \text{if } \hat{t}_k \geq r \\ \hat{t}_k + (r - \hat{t}_k) \cdot c_p & \text{otherwise,} \end{cases} \tag{2}$$

where $0 \leq c_p < 1$ is the *paragraph constant*: it specifies how much additional trust the author reputation confers to the paragraph of the article she modified. Thus, text in modified paragraphs receives an additional trust increment.

2.4 Robust trust

The current implementation of the trust system is a batch one, in which the wiki revision history is analyzed off-line. Our goal, however, is to develop algorithms that are suited for on-line implementation and deployment on live wikis. If the trust system is deployed on a high-traffic, and high-visibility wiki, it most likely will come under attack. We consider two types of attacks: *vandalism* attacks, aimed at destroying the trust information, and *tampering* attacks, aimed at causing the text to increase unduly in trust, perhaps to mask malicious changes. We present here methods that make the trust system robust to such attacks. In making the trust system robust to attacks, we assume that the reputation system itself is reliable, in the sense that it is hard for authors to gain reputation in a short time, without strong justification. Thus, we deal with the robustness problem in modular fashion: this paper concerns itself with a robust trust system, while the problem of implementing a robust reputation system will be dealt with elsewhere.

2.4.1 Vandalism

The algorithms for text trust that we have presented so far are already robust with respect to vandalism attacks in which portions of text are deleted. Deleted text is tracked by the system, as described in Section 2.3.1. Since vandals typically have a reputation close to 0, the trust of the text is lowered by a small amount when the deletion occurs, as the multiplicative factor e^{-rc_k} is very close to 1. When the deleted text is re-inserted, its trust value will be essentially unchanged. In a more malicious version of this attack, vandals can perform extensive text re-arrangements, causing much text to be assigned the low trust value used for block-move endpoints (see the edge effect in Figure 2). To defend against this attack, the on-line system we are developing compares the text of revision v_k with the text of revisions $v_{k-m}, v_{k-m+1}, \ldots, v_{k-1}$; special data structures make this comparison efficient even for values of m that range up to 50 or more. We then identify the past revision v_j that is closest, in edit distance, to v_k. The trust assigned to each word of v_k is then equal to the *largest* of these two trust values:

- the trust value resulting from the edit $v_{k-1} \rightsquigarrow v_k$;
- the trust value computed as if the edit $v_j \rightsquigarrow v_k$ occurred (thus short-circuiting revisions $v_{j+1}, \ldots, v_{k-1}$).

In this fashion, as long as vandalism is reverted within a small number of revisions (no larger than m), the original trust of the text is restored.

2.4.2 Tampering

The above vandalism attacks have the aim of lowering the trust value of text in an article. The attacks can cause visual distractions for the readers of the article, as much text is labeled and colored as low trust, until the vandalism is corrected. Nevertheless, these attacks never cause text to be labeled with too high a trust value. A more malicious type of attack, which we call *tampering attack*, aims instead at raising the trust value of the text of an article, in spite of the fact that the text has not been properly revised by the wiki community of authors.

The algorithms described in Sections 2.2–2.3 are not robust with respect to tampering attacks by high-reputation users. According to the algorithms presented so far, new text inserted by an author A of reputation $r \in [0, T_{\max}]$ initially has the value of trust

$$c_l r + (r - c_l r) c_r + \Big(r - \big(c_l r + (r - c_l r) c_r \big) c_p \Big) < r \ .$$

However, if the author A performs multiple small edits on an unrelated portion of the same article, the trust of this text grows, until it approaches r. Thus, author A could first add arbitrary text to one portion of the article, and then perform multiple small edits to another portion of the article. After such sequence of edits, the arbitrary text would have trust very close to r.

To defend against this type of attack, we allow authors to increase the trust of a word only if they have not already done so recently. Precisely, for each word, we keep track of the list of the last m authors who have increased the trust of the word. When an author A performs a revision, for each word w of the new revision, we first check whether steps (1) (of Section 2.2) and (2) (of Section 2.3.2) would lead to a trust increase for w. If so, we proceed as follows:

- If A appears in the list l associated with w, we leave the trust of the word w unchanged.

- If A does not appear the list l associated with w, we insert A at the beginning of l and, if the resulting list is longer than m, we truncate the list to the first m elements.

This scheme ensures that, after an author raises the trust of a word, at least m different authors need to raise the trust of the word before A can do so again.

The scheme obviously prevents the simple attack in which A tries to raise the trust of the word by editing the article frequently. More subtly, the scheme also prevents A from raising the trust of a word via Sybil (or sock-puppet) attacks [6, 17, 3, 26]. In these attacks, A uses multiple identities (all under her control) to try to raise the trust of the word w. To see this, consider the situation after A raises a first time the trust of w to the value t. After this happens, authors (or sock-puppets) can raise the trust of w further only if their reputation is above t. Since we assume that it is difficult for an author or sock-puppet to acquire reputation, it will be difficult for A to have a sufficient number of high-reputation sock-puppets to cause the trust of A to raise.

We prefer to associate the list of past revisors with each word, rather than with an entire page. All our algorithms are word-based, so this choice leads to a more uniform setting. Moreover, we believe that the word-level accounting we use leads to a more natural, and fairer, setting. For instance, consider the case where A raises the trust of a version v of an article, and shortly afterwards, an author B of lower reputation inserts some text in the article. If A edits the page immediately after B, our word-level accounting enables A to raise the trust of the text inserted by B, while preventing A from raising twice the trust of the text that was already present in v. Indeed, there would be no reason to disallow A from raising the trust of the text inserted by B.

The drawback of word-level accounting is storage: for every word of the latest version of each Wikipedia article, we need to remember the list of the most recent m authors who raised the word trust. To achieve a compact representation, we propose to hash the author identities into 8-bit identifiers (using the 0 value as "empty"); if $m \leq 4$, a list can then fit in a 32-bit integer. An overhead of 32 bits per text word is, in our experience, entirely acceptable. This hashing scheme entails a probability of $1 - (1 - 1/255)^m$ of collision, in which case an author will not raise the trust of the word, even if she did not do so previously. To obviate this, we propose to apply the hash function both to the author identity, and to the word. In this way, the hash collisions would be randomized across the text (the collision probabilities of different words would be essentially independent), and the impact on the overall text trust would be negligible.

We call the trust computed with the help of the anti-tampering algorithm above *tamper-resistant* trust, to contrast it with the *non tamper-resistant* trust described in Sections 2.2–2.3.

3 Evaluation Metrics

There are many possible methods of associating trust with Wikipedia text. In the previous section, we have described one such method, and we have argued that, if not optimal, it is at least a reasonable attempt. The question is: how does one evaluate a trust labeling? A quantitative evaluation of a trust labeling is needed both to compare different versions of the algorithms, and to optimize the values of the various coefficients (c_e, c_l, c_r, c_k, and c_p) involved in the computation of the trust labeling.

The key idea we use to evaluate a trust labeling is that high trust should be associated with stability: if a piece of text is highly trusted, it ought to be less likely to change in future revisions than a piece of text which is labeled as low trust. By defining trust as being related to the stability of the text, we relate trust to the consensus that arises from group collaboration.

Based on this idea, we present various evaluation metrics that measure how well low-trust predicts future text changes. We note that this is a sound evaluation method: the trust labeling of a piece of text is computed entirely on the basis of the *past* history of the text;[1] thus, the correlation between text trust and future text change is entirely due to the ability of trust to be a predictor of text stability.

3.1 Low trust as a predictor of deletions

The most reliable indicator of text instability, in our experience, is text deletion. Not all text change is connected to deletions: text can also be reordered, or subject to insertions. However, when text reordering occurs, all words are preserved, and it is difficult to have an objective measure of how far the disruption carries over from the edges of the moved blocks. Deletions present no such ambiguity: each word is either present in the next version, or is deleted. Furthermore, all major content reorganizations involve text deletions, as merging new and old content requires rewording and restructuring the old content.

Thus, a basic evaluation metric consists in measuring the precision and recall of low-trust with respect to text deletions. For each trust value $t \in [0, T_{\max}]$, we consider the fact of a word w having trust $t_w \leq t$ as a "warning bell", and we ask what is the recall, and the precision, of this warning bell with respect to the event of the word being deleted in the next revision. The recall $recl(t)$ measures the fraction of deleted text that had trust smaller than or equal to t immediately prior to deletion; the precision $prec(t)$ measures the fraction of text with trust smaller than or equal to t which is deleted in the next revision. More formally, let:

- $W^{\leq}_{i,p}(t)$ be the number of words in version i of article p that have trust no larger than t;

[1] The computation uses author reputation, but author reputation can also be computed on the basis of the past history of the text; see, e.g., [1].

- $D^{\leq}_{i,p}(t)$ be the number of words in version i of article p that have trust no larger than t and which are deleted in the revision from version i to $i+1$;
- $D_{i,p} = D^{\leq}_{i,p}(T_{\max})$ be the number of words in version i of article p which are deleted in the revision from version i to $i+1$.

Then, we have:

$$\mathit{recl}(t) = \sum_{i,p} D^{\leq}_{i,p}(t) \;/\; \sum_{i,p} D_{i,p} \qquad (3)$$

$$\mathit{prec}(t) = \sum_{i,p} D^{\leq}_{i,p}(t) \;/\; \sum_{i,p} W^{\leq}_{i,p}(t) \;, \qquad (4)$$

where the summation is taken for all versions of all articles that are used to evaluate the quality of the trust labeling.

While recall and precision of low-trust are good indicators, they suffer from the fact that text can be deleted by vandals, only to be re-added in the next revision. This source of error can be significant: while people intent on improving an article often delete small amounts of text at a time, vandals often delete the entire text of an article. To obtain better measures, we would like to give more weight to deletions that happen due to well-thought-out editorial concerns, rather than vandalism. To this end, we employ the notion of *edit longevity* developed in [1]. The edit longevity $\alpha_{i,p} \in [-1, 1]$ is a measure of how long-lived is the change $e_i = v_{i-1} \rightsquigarrow v_i$ for article p. In particular, if $\alpha_{i,p}$ is -1, then the change e_i is reverted immediately, and if e_i is a deletion, then practically this should not be considered as a valid deletion. On the other hand, if $\alpha_{i,p}$ is close to 1, the change will live through many subsequent revisions, and if e_i is a deletion, then it should be considered as a valid deletion [1]. We use the *edit quality* $q_{i,p} = (\alpha_{i,p} + 1)/2$ to weigh the data points in (5)–(6), thus giving weight close to 1 to deletions that happen due to authoritative revisions, and no weight to deletions performed by vandals (which have longevity -1). We thus define the *quality-weighed* recall and precision of low-trust with respect to deletions as follows:

$$\mathit{w\_recl}(t) = \frac{\sum_{i,p} q_{i,p}\, D^{\leq}_{i,p}(t)}{\sum_{i,p} q_{i,p}\, D_{i,p}} \qquad (5)$$

$$\mathit{w\_prec}(t) = \frac{\sum_{i,p} q_{i,p}\, D^{\leq}_{i,p}(t)}{\sum_{i,p} q_{i,p}\, W^{\leq}_{i,p}(t)} \;. \qquad (6)$$

3.2 Trust distribution of general vs. deleted text

Another quality metric for trust labelings is obtained by comparing the trust value distribution of all text, and of deleted text. Recall that, in our system, we display the text of revisions with a background color that reflects text trust, and which ranges from white for fully trusted text, to orange for text with trust 0. Site visitors are going to use the orange background as an indication that the information may be unreliable. If too much text on an article has orange background, the alert loses effectiveness, as visitors habituate to the constant flagging of text. Thus, we prefer trust labeling in which text, on average, is as trusted as possible. On the other hand, we clearly want text to be flagged as low-trust when it is about to be deleted.

To make these notions precise, we define the following quantities. Given a function $f : [0, T_{\max}] \mapsto \mathbb{R}$ with $\int_0^{T_{\max}} f(t)\, dt < \infty$, and $\rho \in [0,1]$, we define the *ρ-median* of f the quantity a satisfying

$$\int_0^a f(t)\, dt = \rho \int_0^{T_{\max}} f(t)\, dt \;.$$

We also denote with $W^{=}_{i,p}(t)$ the amount of text having trust t in version i of article p, and we denote with $D^{=}_{i,p}(t)$ the amount of text in version i of article p having trust t which will be deleted in version $i+1$. We define the following notations:

$$\mathit{tot\_txt}(t) = \sum_{i,p} W^{=}_{i,p}(t)$$

$$\mathit{del\_txt}(t) = \sum_{i,p} D^{=}_{i,p}(t)$$

$$\mathit{w\_del\_txt}(t) = \sum_{i,p} q_{i,p} D^{=}_{i,p}(t) \;.$$

We assess the quality of a trust labeling via the following quantities, for $\rho \in [0,1]$:

- The *ρ-white point* is the ρ-median of $\mathit{tot\_txt}(t)$.
- The *weighed orange average* is the average value of t for $\mathit{w\_del\_txt}(t)$.

We will use $W_{0.9}$ and Org_{avg} to denote the 0.9-white point and weighed orange average, respectively. Again, the weighing used in the definition of orange average is used to give more weight to deletions that occur in the course of higher-quality revisions.

3.3 Trust as predictor of text life-span

Our final quality metric for the trust labeling consists in quantifying the predictive value of word trust with respect to the subsequent life-span of the word. To measure this predictive value, we sample word occurrences from all versions uniformly at random (applying the algorithm to all words would be computationally very expensive), and we observe for how many consecutive article versions the words are present after their sampled occurrence.[2]

[2] As we have seen in Section 2.3.1, a word in a version can correspond to multiple occurrences in the next version, when text is duplicated. When tracking a word to measure its life-span, whenever the word is duplicated, we track all occurrences separately.

The simplest approach consists in studying the correlation between the trust t of the word at the moment it is sampled, with the life-span l of the word, measured as the number of consecutive subsequent versions in which the word is present. However, such a measurement would be biased by the *horizon effect* induced by the fact that we have only a finite sequence $v_0, v_1, \ldots, v_n$ of versions to analyze. Words sampled in a version v_i, and that are still present in the last version v_n, have a life-span of $n - i + 1$, even though they may live much longer once the wiki evolves and versions beyond v_n are introduced. This horizon effect causes us to under-estimate the true life-span of high-longevity words sampled close to the last existing version of an article.

To obtain a measurement that is unaffected by this horizon effect, we model the life-span of a word as a memoryless decay process, in which the word has a constant probability (dependent on the word, but not on its past life-span) of being deleted at every revision. Thus, we assume that the probability that a word that is alive at v_i is still alive at v_k, for $k \geq i$, is $e^{-(k-i)/\lambda}$, where λ is the half-life of the word under infinite-horizon. Our task is then to estimate the correlation between the trust t that the word has in v_i and the half-life λ of the word. Note that this definition of half-life eliminates the horizon effect due to the finite number of versions.

For every word sampled at v_i, and last present in v_k, with $i \leq k \leq n$, we output a triple (t, l, h) consisting of the trust t of the word in v_i, the life-span $l = k - i + 1$, and the observation horizon $h = n - i + 1$. To estimate λ, we use the following observation: if $l < h$, then the word would have lived for l even under infinite horizon; if $l = h$, then the word has an average life-span of $l + \lambda$ under infinite horizon, since the distribution is memoryless. Let A be the set of triples sampled for a trust level t. Let:

- m be the number of samples in A with $l < h$;
- $M = \sum\{l \mid l < h \wedge (t, l, h) \in A\}$;
- k be the number of samples in A with $l = h$;
- $K = \sum\{l \mid l = h \wedge (t, l, h) \in A\}$.

We can estimate λ via

$$\lambda = \frac{M + K + k \cdot \lambda}{m + k}$$

which yields

$$\lambda = \frac{M + K}{m}.$$

A trust labeling will have high predictive value for life-span if larger values for the trust of the word in v_i correspond to larger values of λ.

3.4 Predicting stability vs. providing visual feedback

The evaluation metrics introduced above quantify the quality of a trust labeling via its ability to predict text instability. While predicting instability is surely an important requirement of a trust system, a trust system in practical use also has another goal: providing visitors with visual feedback on the past edits to articles. While the goals of predicting stability and providing visual feedback are often compatible, there are instances when they are not. As an example, consider the case of an author removing a sentence from a paragraph. Our trust labeling will label low-trust both the end of the sentence preceding the removal, and the beginning of the sentence immediately following the removal. This low-trust labeling, and the resulting orange coloring, is used to make readers aware that some edit has occurred — that text was removed. The low-trust labeling is thus given for feedback purposes, and this use may be at odds with the goal of maximizing its power to predict instability. Indeed, sentences that precede and follow the removal are unlikely to be themselves deleted, so that from a prediction point of view, the labeling is inappropriate.

In our system, we strive for a mix of these prediction and feedback goals. However, our evaluation reflects only the predictive aspect of trust: we do not know how to algorithmically evaluate its feedback value.

4 Implementation

We have implemented a trust tool that computes text trust and provenance for the Wikipedia. The trust tool takes as input an XML dump containing all the text of all the revisions of the Wikipedia; such dumps are periodically made available from the Wikimedia Foundation. The trust tool is written in Ocaml [16]; we chose this language for its combination of speed and excellent memory management. On an Intel Core 2 Duo 2 GHz CPU, our tool is capable of assigning trust to versions of Wikipedia articles[3] at over 15 versions/second, or roughly 1.5 millions versions per day, an edit rate much higher than the one of the on-line Wikipedia [32]. We have run the trust tool over the entire English Wikipedia, as of its February 6, 2007 dump; the results can be viewed on a live demo [29]. To save disk space on the server, the demo contains only the last 100 versions of each article, but all versions were considered in trust computation.

The current implementation of the tool is a batch one. The first step consists in computing the *reputation history* of all Wikipedia authors. When the trust system examines a revision $v_k \rightsquigarrow v_{k+1}$ performed by an author A, it looks up

[3] Measured on a randomly-selected subset of articles with at least 200 versions each.

the value of trust of author A in the reputation history of A, corresponding to the time t_{k+1} when v_{k+1} was created. The trust system uses the reputation of A at time t_{k+1}, rather than the "final" or "average" reputation of A, in order to mimick faithfully the trust computation that is used in the on-line system we are developing.

The reputation histories are computed using the using the *content-driven* reputation system for Wikipedia authors proposed in [1]. In this system, authors of contributions which prove long-lasting gain in reputation, while authors whose contributions are reverted lose reputation. Specifically, whenever an author A edits an article that had been previously edited by another author B, a change in reputation is generated for B: the reputation of B increases if A preserves B's contribution, and decreases if A undoes B's contribution. The reputation system is thus *chronological:* the reputation is computed from the chronological sequence of increments received by authors. The reputation system is such that $T_{\max} = 9$.

Once the reputation histories of all users have been computed, we feed the reputation histories, and the Wikipedia XML dump, to the trust tool. The tool produces as output a *colorized* XML dump, containing the original text annotated with the computed trust and provenance information. The colorized dump is in the same format as the input XML dump, except that two additional markup tags are intersepsed in the text:

- the tag $\{\{$`#t:`$x\}\}$ indicates that the subsequent text has trust $x \in \{0, 1, \ldots, 9\}$ (trust is rounded to the nearest integer for display purposes);

- the tag $\{\{$`to:`$i\}\}$ indicates that the subsequent text was first inserted in version i (Mediawiki assigns to each version a global integer identifier).

To save storage, these tags are not added for each word, but only when the information changes from one word to the next. Adding the trust and origin tags to the Mediawiki markup language without breaking the visual formatting of Wikipedia articles is a minor challenge in itself. The markup language is position sensitive: for instance, the title (`==`) and bullet (`*`) markups only work when they occur precisely at the beginning of a line, and tables have complex rules that determine where extra markup can be added without breaking the table formatting. Furthermore, there is no complete documentation of the language, especially as authors often abuse it: "everything that renders fine, is fine". Inserting the markup properly involved developing a parser for the markup language occurring in practice in Wikipedia articles (including errors and abuses), with the purpose of identifying the places where the tags could be safely inserted.

The colorized XML dump can be loaded in a Mediawiki installation using the standard tools made available as part of Mediawiki (Mediawiki [22] is the software package responsible for implementing the wiki behind Wikipedia). The additional tags are then interpreted by a Mediawiki extension we developed, following the Mediawiki extension framework. We display the trust of each word by coloring the background of the word: white for fully trusted words, and increasingly intense gradations of orange for progressively less trusted text. For text origin, our extension defines a onclick action in JavaScript. When a user clicks on a word, the user is sent to the article version where the word was first inserted. The two types of information, trust and origin, augment each other, and together provide Wikipedia visitors with effective tools to judge the accuracy of article content. The trust coloring focuses visitors' attention to the portions of an article which are less reliable, either because they are very recent, or because they were introduced by low-reputation authors and have been insufficiently revised. The origin labeling can then be used to explore how the unstable information was added to the article.

Towards an on-line implementation

We are currently working on an *on-line* implementation of the trust system, capable of coloring the revisions of Wikipedia articles as they are created. The on-line system will be suited to any MediaWiki-based wiki, and indeed to any wiki, via minor adaptations.

While in the batch system the computation of author reputation histories, and the computation of text trust, happen in two separate passes, in the on-line system author reputations and trust are updated in real-time, every time a new article revision is created. When a revision is created, the on-line system first analyzes the text difference between the revision and the previous article revisions. This information is passed to the reputation system first, which updates the reputation of the authors of previous article revisions, according to the algorithms of [1]. Intuitively, past authors whose contributions are preserved in the latest revision gain reputation, while authors whose contributions have been undone lose reputation. Once author reputations have been updated, the information on text tracking is passed to the trust system, which updates word trust according to the algorithms of Section 2. Thus, in the on-line implementation, every new revision causes reputation and trust values to be updated. We stress that while the batch process performs the updates in two separate sweeps, the on-line and batch systems compute the same values, due to our use of author reputation histories. Thus, the performance figures that we report for the batch system will be directly applicable to the on-line system.

5 Results

Our first step in the performance evaluation of the trust labeling consisted in choosing values for the constants appearing in the trust labeling algorithm. Choosing values for the constants involves balancing the recall and precision of the trust labeling: the recall is a measure of the trust labeling's ability to flag unreliable content, and the precision is a measure of how likely it is that something flagged will turn out to be unreliable. Thus, obvious candidates for optimization were the weighed recall $w\_recl(t)$ and the precision $w\_prec(t)$, for $t \in [0, T_{\max}]$ defined in Section 3. However, this approach was difficult to follow in practice. First, the particular value of $t \in [0, T_{\max}]$ that should be picked for optimization was not clear: which value of trust is low enough, or which shade of orange is dark enough, to constitute a warning? Second, it was not clear to us what would constitute acceptable values of recall and precision.

We found it much easier to reason about how "white" a mature article should be on average, and about how "orange" the deleted text should be: thus, we performed the optimization using the white point and orange average, as defined in Section 3. We let $W'_{0.9} = W_{0.9}/T_{\max} \in [0, 1]$ be the normalized 90%-white-point, and we let $Org'_{avg} = (T_{\max} - Org_{avg})/T_{\max} \in [0, 1]$ be the normalized weighed orange average, where $T_{\max} = 9$ for our system. We wanted to find parameter values that would make the article, overall, as white as possible (maximize $W'_{0.9}$), while ensuring the deleted text was as orange as possible (maximize Org'_{avg}). To this end, we used linear search on the space of the parameters to optimize the value of the *weighed harmonic mean* of $W'_{0.9}$ and Org'_{avg}, i.e., we optimize

$$F(W'_{0.9}, Org'_{avg}) = \frac{2 \cdot W'_{0.9} \cdot Org'_{avg}}{W'_{0.9} + Org'_{avg}},$$

for a set of 100 articles used for training. We use the weighed harmonic function since it weighs both of its arguments evenly. This led to the following values for the parameters, for non tamper-resistant trust:

$$c_r = 0.2 \quad c_l = 0.4 \quad c_e = 2 \quad c_p = 0.2 \quad c_k = (\log 2)/T_{\max} . \tag{7}$$

For the tamper-resistant trust, we choose $m = 3$, so that an author needs to wait until three other authors of similar reputation raise the trust of a word, before being able to raise it herself again. As tamper-resistant trust yields slighty lower trust (as authors are occasionally prevented from raising the trust of words), we compensate by taking $c_r = 0.3$, which yields essentially the same values for the white point and orange average; the other coefficients are as in (7). With this choice, the results we obtained for normal trust, and for tamper-resistant trust, are quite similar. In the figures, we indicate with *NR* the non tamper-resistant trust, and with *TR* the tamper-resistant trust.

We proceeded to evaluate the performance of the trust coloring on a set of 1,000 articles selected uniformly at random among the articles with at least 200 revisions; the articles comprised 544,250 versions all together, for a total of 13.7 GB of text. We focused on articles with long revision histories for two reasons. From a technical point of view, the long revision history enables us to better estimate the predictive power of trust with respect to text stability. From a user-interface point of view, our trust is especially useful for mature articles: it is relatively easy for visitors to conclude that incomplete articles, with short revision history, cannot (yet) be trusted.

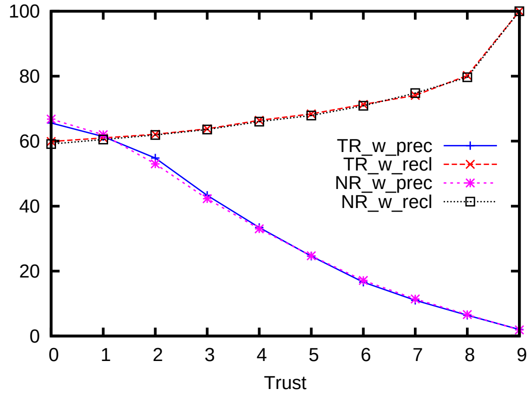

Figure 3: Low-trust as a predictor of deletions: quality weighed precision and recall.

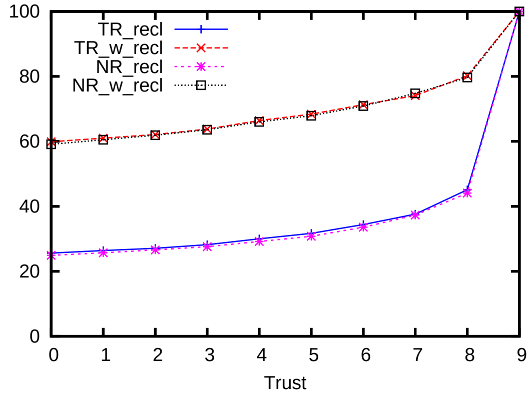

Figure 4: Comparison of recall and weighed recall.

Figure 3 gives the quality-weighed precision and recall of low trust with respect to text deletions. We see that the recall is always at 60% or above; in practice, a mid-range orange background, which is sure to attract a reader's attention, is able to warn the reader to 2/3 of the text that will be deleted in the next revision. We believe that this is a good performance figure, given that text can be deleted for many reasons other than poor quality, such as rewording: thus, some deletions are never likely to be anticipated by low trust. The precision figures give the probability that text marked as low-trust will be deleted in the very next revision; low precision figures would be a sign of excessive warnings to visitors. We see that text with trust 0 has a 2/3 probability of being deleted in the next revision, and text with mid-level

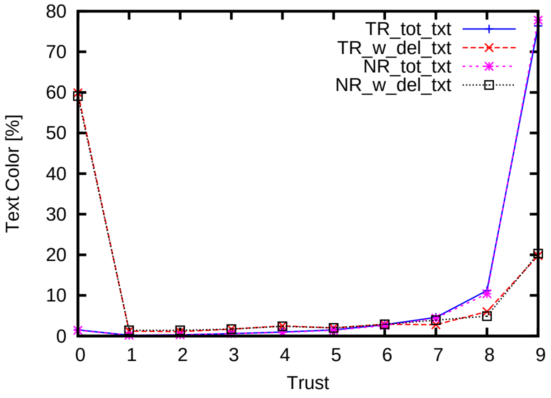

Figure 5: Color of general and deleted text.

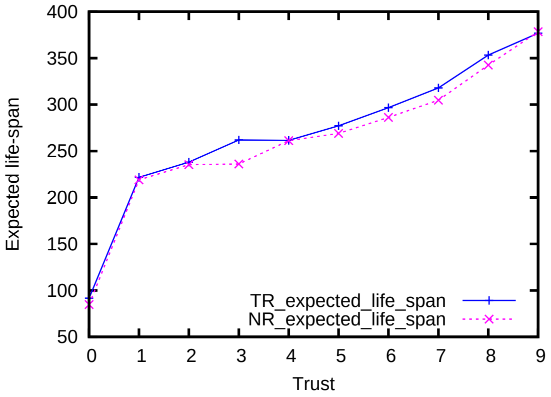

Figure 6: Expected future life-span λ of words.

trust has a 1/3 probability of deletion; we consider this to be an acceptable level, especially since not all text that will be deleted is going to be deleted in the very next revision. In Figure 4 we compare weighed and unweighed recalls: as we see, if we also include deletions due to vandalism ($recl$), our recall drops, reflecting the fact that such vandalistic deletions are hard to predict.

The color profiles of general and deleted text are compared in Figure 5. We can see that deleted text, on average, is much lower in trust: indeed, the average trust of deleted text was 2.96, while 90% of text had a trust above 7.60 (out of a maximum of $T_{\max} = 9$).

Figure 6 depicts the correlation between the trust of a word occurrence, and the subsequent life-span of the word. The data is obtained by random sampling of word occurrences, and tracing the future of the word from the sampling point. We note that the trust is the trust of the *word occurrence:* over the subsequent life-span, the word trust may well vary (and typically increases, as the article is revised). We see that there is a clear correlation: higher trust corresponds to a longer expected life-span. We also see that there is a sharp increase in expected life-span as we go from words labeled with trust 0 to words labeled with trust 1. This can be explained by the high “early mortality” of words with trust 0: over 60% of them, as indicated by the recall graph in Figure 3, do not make it to the next version.

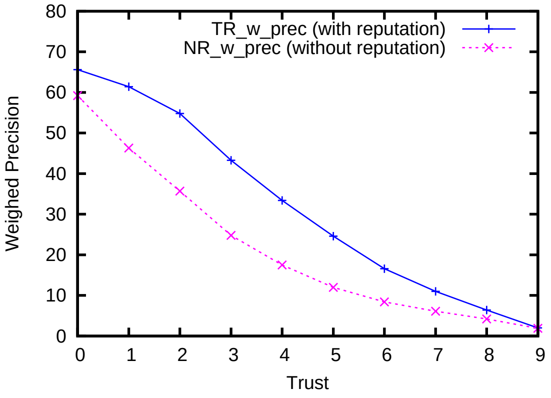

Figure 7: The weighed precision with and without reputation systems.

We also evaluated the magnitude performance improvement due to the use of the author attention modeling presented in Section 2.3.2. To our surprise, we discovered that the author attention modeling does not appreciably improve the results, in spite of introducing additional degrees of freedom in the trust algorithms. We believe this is due to the fact that authors usually edit the sections of an article that have received the most recent edits. Thus, outside of the paragraph being edited, there is not much text which can benefit from a trust increase, and distinguishing between edited and non-edited paragraphs has little effect.

5.1 Trust quality in absence of a reputation system

The reputation system provides two key benefits to our trust system: it provides information on the quality of the authors, and (most importantly) it enables us to obtain a system that is resistant to tampering. The present evaluation, however, is performed on past data, where tampering cannot have occurred, as authors were unaware even of the proposal for such a system. This provides us with the opportunity to evaluate the quality improvement of the trust system that can be ascribed to the use of a reputation system.

To this end, we compared the performance to the regular trust system, with the performance of a modified trust system that does not rely on a reputation system, and instead assigns everybody, from anonymous visitors to well-established editors, the maximum value of trust. Fresh text, as well as block-move edges, received initially trust 0,[4] and the trust of text would then increase according to the algorithms of Section 2 (no change was made to the trust algorithms). We

[4] Had we used a trust value greater than 0 as initial value, no text would ever get trust 0.

note that this is in fact equivalent to using the *age* of text, measured in number of revisions, to compute the trust. We chose coefficients for the trust computation that would yield an weighed orange average similar to the one obtained using a reputation system.

The trust labeling computed without the aid of a reputation system performed worse than the one that made use of the reputation system of [1]. The performance gap was most noticeable with respect to the precision, as illustrated in Figure 7: for trust 4, for instance, the precision was nearly double (33%) with the reputation system than without (17.5%). The gap for recall was narrower: for trust 4, the quality-weighed recall was 66% using a reputation system, and 72.5% without. Furthermore, while deleted text had similar colors, the average text was noticeably more orange in the tests not using the reputation system: the 90% white point went from 7.6 using reputation, to 5.43 when reputation was not used.

This performance difference can be explained as follows. One of the benefits of using a reputation system is that text which is inserted or moved by high-reputation authors receives a non-zero initial value of trust (in our system, $0.616 \cdot 9 \approx 5.5$). This reflects the fact that high-reputation authors are statistically more likely to perform good contributions [1]. If we do without a reputation system, all newly inserted or rearranged text instead has trust 0 initially. This makes the text lower-trust overall (thus the lower 90% white point), and this decreases precision, since among the low-trust text is plenty of text that is due to authors who are statistically likely to perform good contributions.

5.2 Discussion

The results on precision and recall, word longevity prediction, and trust distribution overall indicate that the trust we compute has indeed a predictive value with respect to future text stability. As mentioned in the introduction, this is an indication that the trust system provides valuable information; the visitors to our on-line demo seemed, in anedoctical fashion, to corroborate this finding.

A natural question is whether a similar performance could be obtained more simply by considering the “age” of text in articles. To answer this question, first consider how “age” can be measured. There are two natural choices: to measure text age via the number of revisions, or via the amount of time, for which the text survived.

Consider first the case of age measured via the number of revisions for which text survived. This is the scenario described in Section 5.1 above, and as indicated there, it leads to somewhat inferior performance. The biggest drawback of this approach, however, is that it would lead to a trust system that is extremely susceptible to tampering: to raise the trust of a portion of text, all an authour would need to do is to edit the article multiple times, perhaps with the help of sock puppets.

Measuring age as the amount of time for which text survived, on the other hand, would lead to problems due to the varying rate at which Wikipedia articles are edited. Choosing a fast time-constant for trust increase would most likely work well for popular articles, but would enable text in seldom-visited, seldom-edited pages to gain quickly trust in a near absence of actual revision. Choosing a slow time-constant, on the other hand, would prevent text on topical articles, subject to frequent edits, from gaining much trust.

Furthermore, we note that even if a notion of text age would be adopted, perhaps renormalized for each article according to the edit rate of the article, this would not lead to a noticeable simplification of the actual trust system. In terms of implementation complexity, the main challenge in the trust system, as in the reputation system of [1], consists in parsing and tracking the text across revisions in an efficient fashion. This parsing and tracking would be required even if some notion of age was adopted as a trust metric, so the simplification would be more apparent than real.

In conclusion, we believe that the trust system we proposed provides a good balance between implementation complexity, performance, and resistance to tampering.

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