SmartWiki: A Reliable and Conflict-Refrained Wiki Model Based on Reader Differentiation and Social Context Analysis

Haifeng Zhao¹*, William Kallander¹, Henric Johnson², S. Felix Wu¹,²

Abstract

Wiki systems, such as Wikipedia, provide a multitude of opportunities for large-scale online knowledge collaboration. Despite Wikipedia’s successes with the open editing model, dissenting voices give rise to unreliable content due to conflicts amongst contributors. Frequently modified controversial articles by disagreeing editors leads to inconsistent information incorporated into knowledge bases. To address this well known issue, Wikipedia administrators are able to intervene and lock overheated controversial articles, however in doing so, they introduce their own biases. These actions in turn undermine both desirable neutrality and freedom policies of Wikipedia. In this paper we present an open Wiki model, called SmartWiki, which bridges readers closer to reliable information while also allowing all editors to freely contribute. From this perspective, the conflict issue results from presenting knowledge in an identical way to all readers, without regard for differences in their knowledge-seeking motivations and social context. This in turn negatively impacts the knowledge perception of readers. To address this, SmartWiki therefore considers two types of readers, “value adherents” who prefer simpler and more compatible viewpoints and “truth diggers” who crave deeper understanding of a topic, including both sides of controversies. Social context, in the form of reader and contributor social background and relationship information, is then embedded in both knowledge representations to present
readers with personalized and credible knowledge. This approach thereby considers the readers’ information need level, their psychological acceptance, as well as contributor biases, in presenting reliable content to readers. Our experiments and system analysis prove that the knowledge representation models can not only reduce conflicts and reinforce neutrality policies, but also have great potential to solve a series of content reliability problems in open Wiki systems such as vandalism and minority opinion suppression.

**Keywords:**
Knowledge Representation, Online Social Network, Wikipedia, Natural Language Generation

---

1. Introduction

1.1. Background

Wiki systems are widely-used online collaborative applications which allow multiple contributors from diverse backgrounds and dispersed geographic locations to collaborate in creating and editing manuals, books, and other public knowledge bases. Among the numerous Wiki ecosystems, Wikipedia is probably the most widely known. Its essential idea, that a useful encyclopedia of knowledge can be created by allowing anyone (even anonymous users) to create and edit articles, is predicated on the principles of openness and neutrality. Wikipedia has grown to over 3.9 million articles (in English alone) with millions of contributors (as of May 2012). In the face of such scale, the openness policy has invited conflicts, or the inclusion of bias, debate, and abuse inside Wikipedia articles covering controversial topics.

Opening unrestricted editing access to everyone makes this lofty goal of maintaining a Neutral Point Of view (NPOV) overly optimistic due to the inevitable biases and idiosyncrasies of human editors. Instead of collaborating harmoniously, some individuals attempt to dominate “their” articles and nullify all previous edits with which they disagree, often forcing administrators to lock down the editing access of those articles in contention. However, this “lock” method is, by itself, also at odds with the NPOV policy since Wikipedia administrators must subjectively choose a preferred article version before freezing such articles.

Wikipedia assumes that “the articles are agreed on by consensus”\(^3\). This

assumption treats unreliable content as a consensus problem, and thereby posits that, while misleading information can and will be contributed, over time the quality will improve as editors reach consensus and the resulting article moves toward a “stable” version. This effect works well in mitigating certain types of unreliable content, such as vandalism, as the majority of editors are honest and responsible. However, it remains vulnerable to disputes existing in hundreds of thousands of pages, especially those related to contentious historical, religious and political subjects. Even if an article appears to be “stable”, it may still retain bias, as some earlier contributors may have preferred to throw in the towel rather than engage in endless editing wars. With regard to a single controversial article, there may be hundreds of editors with considerably diverse evidence, statements and viewpoints to present. For the vulnerable reader who is unfamiliar with a topic presented in an article, how does s/he evaluate the credibility of information from a plethora of unknown or anonymous editors?

Take a locked page “Muammar Gaddafi” (the former leader of Libya) for example. Figure 1 shows two historical updates which resemble one another but have obviously different sentiments and evidence:

The lefthand update positively expects the U.S. government to restore
diplomatic ties with Libya and implies that the country is not supporting terrorism. However, the righthand update suggests that the U.S. government would only restore diplomatic ties contingent upon the cessation of Libya’s weapons of mass destruction programs. Meanwhile, the update on the right also puts forth evidence that denounces Libya’s autocracy as further supporting terrorism. Both of the prose contributors are anonymous. Which update should be more trusted? While Wikipedia authorizes administrators to evaluate opinions and evidence on some controversial topics, there are no guarantees that these “experts” will completely avoid personal bias and present universally fair viewpoints to readers, which is at odds with the NPOV policy.

The current strategy for maintaining NPOV sacrifices reader control in favor of contributors. This strategy exerts effort to ensure complete accuracy for all readers, which is impossible in cases where subject matter experts disagree. The critical issue here is that not all readers have the same goal in seeking knowledge about a topic. This important factor is overlooked by the current NPOV strategy, where the judgement and decision making of readers is ignored. At a high level, we draw a distinction between two different motivations for readers, where the degree of discernment for the truth is starkly contrasted.

In the more general case, we observe that (lenient-type) readers refer to information in Wikipedia without overconcern about absolute truth in depth, especially when the article is irrelevant to their everyday lives. In this article, we name them as “value adherents.” From the psychological perspective, readers have a tendency to favor information that confirms their beliefs or hypotheses [1]. Moreover, such judgements and deliberations about trust are subject to social influences, since people are social by nature [1]. Social context factors, including social background and interpersonal relationships, play important roles in the adoption of content [2], and are even make people change in belief or behavior [3, 4].

The importance, trustworthiness, and compatibility of the same pieces of information vary significantly to readers with different social contexts. The diversity of social contexts stretches across many variables, such as social relationships, cultural factors, ethnicity, education, and other human factors. Thus, when facing the dilemma of conflicting information from multi-

ple sources, people tend to believe friends or authorities with whom common values and/or similar social backgrounds are shared. These social context factors are absent in the knowledge representation model of traditional Wiki systems.

In contrast to the value adherents described above, there are readers who crave absolute truth in depth. They are skeptical, critical thinking, and open-minded in their willingness to take a holistic view of controversial opinions before allowing themselves to take a stand. In this article, we name them as “truth diggers”. They refer to Wikipedia seeking solely accurate information and welcome conflicting opinions on controversial topics that deepen their understanding. Unfortunately, the knowledge representation model in traditional Wiki systems cannot efficiently filter and organize conflicting opinions. Worse, controversial topics that have been administratively locked may even undermine the NPOV policy in terms of their needs. Richard Rorty suggested that “If we take care of freedom, truth will take care of itself.” [5]. Censoring unfavored editors undermines the discovery of truth for this type of reader. These readers would rather view a clear and well-organized knowledge representation model that reveals conflicting opinions so that the merits of differing opinions may be weighed before adopting a standpoint for themselves.

1.2. Contribution

In this paper, we introduce an alternate Wiki system, SmartWiki, which presents two knowledge representation formats for simultaneously meeting the needs of both kinds of readers. For “value adherents” in this article, SmartWiki assigns different priorities for presenting knowledge content which accounts for their social context with respect to article contributors. This allows for customization of content in keeping with their preference for information consistent with their beliefs (and those of their socially proximate fellows). We assert that if more editor/contributor social context information behind contributed content such as editor background, friendships, and interactions were considered when presenting knowledge to different readers, it would guide the Wiki system to better decide what pieces of knowledge are important and meaningful to different readers. For “truth diggers”, SmartWiki leverages semantic web and Natural Language Generation (NLG) technologies to generate an interface which consisely organizes both supporting and opposing arguments of disputes within an article’s contributions.
The uniqueness of this paper rests on the customization of the presentation layer of online knowledge representation systems by differentiating readers and incorporating social context to prioritize trustworthy information. In addition, this approach offers a solution for redressing other misbehavior in Wiki systems, such as vandalism and minority opinion suppression. Previous research efforts studying the conflict problem in Wikipedia [6, 7, 8] have focused on analyzing and visualizing conflict patterns rather than redressing the content reliability problem and ignore different reader motivations. In this paper, our primary focus is resolving conflicted viewpoints by considering reader information needs, which remains a problem lacking an effective solution.

The rest of this paper is laid out as follows. First, Section 2 introduces the solution and key components of providing compatible information to value adherents. Next, Section 3 describes the summary board disclosing conflicting viewpoints by leveraging NLG techniques for truth diggers. Section 4 demonstrates the effectiveness of SmartWiki with three case studies and two simulations. Section 5 further discusses the evaluation of the system, concerns of personalization, and its influence on the other Wiki problems. After reviewing related work in Section 6, we summarize our conclusions and discuss next steps in Section 7.

2. Read What You Trust By Leveraging Social Context

As we mentioned in previous section, people have a tendency to favor information that confirms their beliefs or hypotheses [1]. Some people rely on local media, some prefer CNN, and some prefer international newspapers. Common values and compatibility are more important to them than hidden truth, especially when they budget limited time to exploring a topic and/or the topic has little immediate relevance to them. We refer to this kind of readers as value adherents. A good knowledge representation for value adherents should reflect their confirmation bias. In our view, confirmation bias strongly relates to social context, including social background and social relationship with others. SmartWiki leverages social context to differentiate the conflicting parties within a controversial article and present credible knowledge to different groups of these readers.

SmartWiki combines three components to provide compatible information in knowledge representation: first, the construction of an appropriate social context is fundamental to uncovering the hidden factors behind contribut-
ed knowledge; second, an efficient algorithm is necessary to identify editor communities which have diverged from each other; and finally, a readable and customizable knowledge presentation layer reflecting reader-compatible or desired "credible" viewpoints. In this section, these three components will be explained in detail.

2.1. Social Similarity Network Construction

The elements of social context include relationships, interactions, gender, ethnicity, education, profession, and the communities in which we live. In SmartWiki, we separate these elements into two segments and represent each segment with a separate network. The first segment of social context is interpersonal social information, such as affinity, relationship and other forms of interaction, which we refer to as the trust network. We avoid using the term "friendship network", because we consider friendship to be a non-directional relationship, whereas trust has directionality in that the same level of trust is not necessarily reciprocated. The second segment is individual social information, such as culture and background, where edges are imparted between two individuals who share background features in common, such as identical ethnicity or common education. We refer to this latter segment as the background network.

Thus, SmartWiki constructs a trust network using interpersonal social information and a background network using individual biographical features. The initialization of social context information could be imported from an existing online social network (e.g. Facebook) as we did in our previous paper [9] and then updated within SmartWiki. Assuming that we have already acquired the two kinds of social context information, we now focus on the functions and maintenance of the two networks separately.

Suppose we have a trust network $G_t(V, E)$ with users represented by vertices and weighted edges simulating the relationship intensity and interaction among users. In our model, this forms a fully connected directed graph. In $G_t(V, E)$, edge weights are determined by trust intensity and are influenced by user interactions. There are many possible methods to evaluate the trust intensity from $u_i$ to $u_j$. Without loss of generality, we propose a simple measure herein to calculate and update trust values. Every user $u_i$ keeps track of a trust value $\text{trust}(u_i, u_j) \in [0, 1]$ to each other user $u_j$. By default, the trust value $\text{trust}(u_i, u_j)$ is initialized as $\alpha$ (e.g., 0.5 in our experiments) if $u_i$ has never provided feedback to $u_j$’s editing. If $u_i$’s feedback to $u_j$’s editing
is \( \gamma \), the trust value from \( u_i \) to \( u_j \) is dynamically refreshed as:

\[
\text{trust}(u_i, u_j) = \frac{\text{trust}(u_i, u_j) + \gamma}{2}
\]

\( \gamma = \begin{cases} 
1.0 & \text{positive feedback} \\
0.0 & \text{negative feedback} 
\end{cases} \)

That is, the more positive feedback \( u_i \) gives to \( u_j \), the higher \( \text{trust}(u_i, u_j) \) will be, implying the accrual of preference of \( u_i \) for \( u_j \)'s contributed content.

Aside from the trust network, the background network also plays an important role in knowledge acceptance. Social background, such as gender, ethnicity, nationality, profession, and other similar factors potentially produce viewpoint divergence among people. We assume that, even without direct friendship, two people with similar social backgrounds are more likely to agree on a controversial issue than two people with different social backgrounds.

These social background values are often categorical in nature, rather than numeric values. A key characteristic of a categorical attribute is that the values are not inherently ordered. For example, the category of “Geography” may contain values like “California”, “Massachusetts”, and so on. To calculate the background similarity of two users, a categorical similarity measure is required. Anderberg [10] introduced a categorical similarity measure, which assigns a higher similarity to rare matches, and lower similarity to rare mismatches. The only limitation of the Anderberg measure is that each object may only possess a single value on an attribute. SmartWiki adapts the Anderberg measure to accept multiple-value attributes. If \( N_m \) denotes the count of all attribute values having appeared on the \( m^{th} \) category, and \( p_m(A_k) \) denotes the probability of the attribute value \( A_k \) in the \( m^{th} \) category, \( p_m(A_k) \) can therefore be computed by dividing the frequency of \( A_k \) (denoted by \( f(A_k) \)) with \( N_m \) as in Equation 2:

\[
p_m(A_k) = \frac{f(A_k)}{N_m}
\]
Equation 3 shows:

\[
S(X, Y) = \frac{\sum_{m=1}^{d} \sum_{A_k \in U_m} \frac{1}{p_m(A_k) f(A_k) + 1} |W_m|}{\sum_{m=1}^{d} \sum_{A_k \in U_m} \frac{1}{p_m(A_k) f(A_k) + 1} |W_m| + \sum_{m=1}^{d} \sum_{A_k \in V_m} \frac{1}{p_m(A_k) f(A_k) + 1} |W_m|}
\]  

(3)

where

\[
U_m = X_m \cap Y_m \\
V_m = X_m \cup Y_m - X_m \cap Y_m \\
W_m = X_m \cup X_m
\]  

(4)

and \(X_m, Y_m\) are respectively the values sets of \(X\) and \(Y\) on the \(m^{th}\) category.

Similar with respect to the Anderberg measure, this adapted measure assigns higher similarity to rare matches, and lower similarity to rare mismatches. The range of \(S(X, Y)\) is \([0, 1]\).

To take advantage of both trust network and background network, we use a measure named “social similarity” in SmartWiki, which linearly combines both similarity measures as described in Equation 5:

\[
social\_sim(u_i, u_j) = \theta_1 \times trust(u_i, u_j) + \theta_2 \times S(u_i, u_j)
\]  

(5)

with \(\theta_1 + \theta_2 = 1\).

Social similarity may therefore be seen as the weighted combination of both trust network and background network similarities. If we consider social similarity as a directional relationship, we build a new graph \(G_{social}(V, E)\) which unifies both interpersonal and individual social context information.

2.2. Discovery of Credible and Compatible Editors

We turn our attention now to evaluating the importance and compatibility of knowledge information to different value adherents readers based on their social context. In our approach, we analyze editors rather than articles due to current limitations of Natural Language Understanding (NLU) technologies. In an ideal world, knowledge in Wikis would be represented semantically, allowing fine-grained knowledge facts to be extracted and evaluated for inclusion in a reader’s view of the knowledge (Similar to Ontowiki...
[11] but without the limitation of only being able to handle simple cases). However, NLU is not mature enough to accomplish this task with sufficient accuracy. Therefore, instead of analyzing the content directly, SmartWiki analyzes contributors as a proxy for subjective attitudes in dividing up the content.

SmartWiki separates contributors into groups and presents (to a reader) the information provided by an editor group which is most compatible and credible to that reader based on previous interactions and background similarity. More specifically, for each article requested by the reader, it first clusters the article editors based on social similarity to magnify the consensus within each group. Then, it evaluates which editor cluster is most similar to the reader and presents the textual content based on the aggregated contributions of members that comprise this closest cluster.

As described in Section 2.1, social context information is embedded in $G_{social}(V, E)$, therefore we want to find a partition algorithm on the graph. This partition can be formalized by the mincut problem. Given a weighted graph described by matrix $A$ and a clustering $C = \{C_1, C_2, ..., C_k\}$, we can calculate the weighted cut by:

$$WCut(C) = \sum_{k=1}^{K} \sum_{k' \neq k} Cut(C_k, C_{k'})$$

(6)

where

$$Cut(C_k, C_{k'}) = \sum_{i \in k} \sum_{j \in k'} A_{ij}$$

(7)

Usually, Equation 7 is normalized to counteract outliers as follows:

$$Cut(C_k, C_{k'}) = \sum_{i \in k} \sum_{j \in k'} \frac{A_{ij}}{vol(C_k)}$$

(8)

where $vol(C_k)$ is the combined weight of all edges in $C_k$.

So the goal of the mincut problem is to find a clustering $C*$ such that:

$$WCut(C*) = \min_C WCut(C)$$

(9)

An approximation to this mincut problem is spectral clustering [12], which recursively partitions the data set by removing edges and evaluating the mincut until $k$ clusters are identified. The general process of spectral clustering
contains two steps: first, compute the unnormalized Laplacian matrix $L$ from
the weighted adjacency matrix $W$; and second, apply the k-means algorithm
to cluster the first $k$ eigenvectors of $L$ into $C = \{C_1, C_2, \ldots, C_k\}$. SmartWiki
adopts the normalized spectral clustering introduced by Shi and Malik [13]
to compute eigenvectors. The approximated clustering result is subjected to
the centroids of the k-means algorithm.

As a special case of spectral clustering, if the number of clusters is two,
then the k-means algorithm is not necessary. The solution can be given by
the second smallest eigenvector $f$ of $L$. In order to obtain a partition of the
graph we need to re-transform the real-valued solution vector $f$ of the relaxed
problem into a discrete indicator vector. The simplest way to do this is to
use the sign of $f$ as the indicator function:

$$
\begin{align*}
    v_i & \in C & & \text{if } f_i \geq 0 \\
    v_i & \in \overline{C} & & \text{if } f_i < 0
\end{align*}
$$

SmartWiki accepts this (sign) property and sets the default clustering
number as two, as it regards controversial articles as polarizing editors into
either positive or negative camps. Note that the number of clusters may also
vary or be customized according to specific scenarios.

The editor clustering process employed by SmartWiki equipped with spec-
tral clustering is summarized in the following steps:

1. From $G_{social}(V, E)$, which contains all the contributors of a Wiki, a
   subgraph $G_{article}(V', E')$ is extracted with nodes $V'$, which are editors
   specifically related to the article.
2. Perform spectral clustering on the subgraph $G_{article}$ to produce a pair
   of clusters.
3. From the pair of clusters, choose the closest cluster to a reader as the
   most credible editor group with regard to the article. The reader’s
distance to a cluster depends on the average of his/her social similarity
   with everyone in a particular cluster.

Thus, after the clustering process, SmartWiki recognizes the editor group
most likely to be compatible and credible to the reader. Even though the
closest cluster may contain some untrustworthy editors (due to noise in so-
cial similarity values), the reader still has a high probability of acquiring
his/her most compatible information. Moreover, if the reader does not like
the provided content, his/her optional feedback will influence the decision of
SmartWiki when choosing an editor cluster for him/her in future interactions.
2.3. Format of Knowledge Presentation

We discuss the content and format of the knowledge information that is to be provided to the value adherents in this section. As we mentioned in Section 1, the knowledge presentation of an article provided by traditional Wiki systems like Wikipedia is the latest historical text version, which is easy to implement with current technology. It is much harder to distinguish inconsecutive or incomplete natural language information spread over several (or all) historical article versions and then assemble and organize these pieces of knowledge in a way as smoothly coherent and readable as a Wikipedia’s latest revision article presentation. The problem is exacerbated by the fact that the finest granularity of knowledge representation in current popular Wiki systems is the free-text of an article. Bias is easily hidden in the narrative, and the technologies for re-writing the prose of an article to remove subjective bias are in their infancy.

To utilize the power of social context, SmartWiki makes a compromise by presenting knowledge in an adapted article version. The adapted article version, with similar readability of a Wikipedia latest revision article, contains the most accepted historical versions of paragraphs contributed by the most compatible editor cluster. Specifically, SmartWiki breaks down the original Wiki article into paragraphs, and for each controversial paragraph, SmartWiki allows editors to provide votes on all historical versions through their modifications and contributions. It then combines three factors to decide which historical version of a paragraph is most popular with the editor’s cluster. These three factors include the number of positive and negative votes \((FB \in \{-1, 1\})\), the social similarity \(SIM\) between a reader and each voter, and the time delta of each paragraph version. Then SmartWiki chooses a paragraph version \(v_i\) with the highest score \(\tilde{S}\) and presents it to the reader.

A simple formula is provided in Equation 11 to combine the three factors described above, which favors newer historical modifications, and normalizes the range of the trust score to lie between \([-1, 1]\):

\[
\tilde{S} = \sum_{e_i \in E} FB(e_i) \times SIM(r, e_i) \times \left(1 - \frac{\arctan(\Delta)}{\frac{\pi}{2}}\right)
\]

(11)

where \(r\) is the current reader, \(E\) is the set of all compatible editors who provided feedback to the historical version and \(\Delta\) is the time difference.

Intuitively, the score \(\tilde{S}\) for each paragraph version assumes that the higher the number of trusted editors who provided positive feedback, and the
more recent a historical version is, the more reliable the paragraph is to the reader. In this way, prose for a readable article with credible paragraphs is produced.

One advantage of the adaptive article technique is that it produces paragraphs that read as smoothly as a traditional Wiki, while presenting more credible and compatible knowledge. Nevertheless, the weaknesses of the adaptive article approach are that transitions between paragraphs become disjoint, and partial knowledge omissions occur in cases where the most popular paragraphs do not fully include all credible knowledge content. In the next section, another knowledge representation model designed for “truth digger” type reader, introduced as a “summary board”, mitigates these disadvantages. SmartWiki thereby provides the flexibility to handle the case where readers transition from “value adherent” to “truth digger”, by presenting a view which clarifies the issues in contention for both kinds of readers.

3. Revealing The Disputes with Auto-Generated Summarization

Having satisfied the needs of “value adherents”, we now turn our attention to the more rigorous type of readers who require stringent information source attribution and unbiased reports. Unfortunately, it is quite difficult, if not impossible, for either the system or even an expert to identify the truth behind a debate. To address this need for these “truth digger” type readers, we propose a knowledge presentation model which reveals viewpoints and evidences from different standpoints in a well structured format, so these readers may easily perceive the divergence and determine the truth for themselves.

3.1. Generalization

Traditional Wiki systems, such as Wikipedia, provide a “discussion board” where editors interact to perform editor functions such as offering opinions about contributions, complaining to administrators, or arguing their viewpoints. However, the loose-structured knowledge presentation format of the discussion board offers little in terms of readability and topic comprehension from the outside reader’s perspective. Unlike traditional Wiki systems, SmartWiki provides a “summary board” instead of (or in addition to) the “discussion board” to address disputes. The difference between a summary and discussion board is that the latter is limited to the chronologically ordered edits to the article content, including historical modification and
pending changes. In contrast, the summary board organizes the content to reveal the divergence of knowledge and contributor viewpoints within.

This summary board is composed by using information extraction (IE) and natural language generation (NLG) technologies. NLG technologies involve the analysis, mining, and production of natural language. Natural language generation (NLG) is the inverse of IE: from structured data in a knowledge base, NLG techniques produce natural language text tailored to the presentational context and the target reader. Using the widely-known Semantic Web as an example, it intends to make information on the information available in the world wide web more usable by bridging the gap between natural language prose and the underlying facts contained within. In this model, factual statements are annotated with tags that disambiguate meaning and structure. This, in tandem with a domain model specification of concepts and their relationships in the form of an ontology, allows computers to reason about content buried within editor contributions. Further, the fused knowledge from both the content contributors and machine reasoning may then be used to generate human readable text. By combining a simple ontology of disputes with a simple NLG method, SmartWiki produces a knowledge presentation format that clearly enumerates divergences within an article, as well as contributor supporters and opponents with respect to those divergences.

3.1.1. The Ontology of A Dispute For The Summary Board

The ontology of a dispute contains entities which reveal the conflicting topic, parties and supporting evidences. Here are the list of entity nodes:

- Dispute: Descendent of Summary Board. Attributes: setup time, source reference in article, brief, supporter number, opponent number
- Proponents: Descendent of Dispute. Attributes: IDs, social composition
- Proponent: Descendent of Proponents. Attributes: nationality, religion, ethnicity, social similarity
- Opponents: Descendent of Dispute. Attributes: IDs, social composition
- Opponent: Descendent of Opponents. Attributes: nationality, religion, ethnicity, social similarity

14
• Evidences: Descendent of Proponent and Opponent.

• Evidence: Descendent of Evidences. Attributes: content, reference, supporter IDs

Every node of the dispute ontology is an entity which can be associated with the attributes describing the properties, features and characteristics of the object. Take a proponent node as an example, its attributes include ethnicity, nationality, education, and other social background information as well as social similarity to the reader as calculated by SmartWiki. The dispute node includes the attributes, such as brief, creation date and popularity. Figure 2 shows the ontology of the dispute node.

A summary board assembles all disputes in sequence. With the exception of the dispute node, the readers may expand or collapse entity nodes to allow for flexibility in reading certain pieces of information. As nodes with smaller granularity are expanded, more detailed information is revealed. In
this way, the summary board lends flexibility to text generation. When the number of disputes is large, limiting the text transformation to only the top level nodes allows the reader to get a coarse-grained big picture view without overwhelming the unfamiliar reader with too many details. The fully generated summary is also achievable by a depth-first traversal of all the dispute nodes in the summary board as each node describes its own ontology attributes in natural language.

3.1.2. The Messages Conveyed by the Entity Nodes

The summary board in SmartWiki currently consists of seven node types, where each type of node corresponds to an entity concept. The messages conveyed in each node covers its entity attributes. Therefore, nodes may cover overlapping information with other nodes.

The information presented by a DISPUTE node includes the subject of the dispute, its quote in a Wiki article, when and who initiated the dispute, the number of editors joined in the discussion and the size number of two conflicting groups. The PROPONENTS node presents the IDs and social composition of the proponents. By expanding a proponent’s ID, the reader retrieves the personal information of the editor, e.g., nationality, religion, ethnicity and social similarity with the reader, as well as the evidences he/she provided. The EVIDENCES node can be expanded by EVIDENCE nodes, whereupon a reader may obtain a full version of each instance of evidence, including the provider, reference(s), and who supports the evidence. The messages conveyed by the OPPONENTS node and OPPONENT nodes resemble this same scheme.

3.2. Text Generation For The Ontology

NLG usually can be divided into three major components. The first component is Document Planning. Document Planning decides what information to mention in the text and the overall organization of information to convey. The second component is Lexicalization which takes care of word choice, aggregation and referring expression. The third component is Surface Realization. It puts words into correct forms based on syntax and morphology so that the text could be read as natural as possible.

NLG techniques involve complicated knowledge of linguistics which is beyond the focus of this paper. The purpose of leveraging NLG in SmartWiki is to reveal the battle of editors and their underlying identities to readers.
In this paper, we mainly focus on the general process of document planning and microplanning without delving too deeply into linguistic details.

3.2.1. Document Planning

Document Planning is concerned with the problem of deciding what content is to be communicated in constructed text and structuring a document to order the information to be conveyed. In SmartWiki, this is the most influential component of NLG.

Since the goal of the summary board in SmartWiki is to reveal disputes and their corresponding opinion groups to readers so that they can be aware of the battles and take a stand, the content determination techniques of NLG in the summary board includes the following pieces of information:

- The disputes of each controversial article
- The statistics of standpoints for each dispute
- The social context information of each opinion contributor and the evidence s/he provided

The dispute ontology as discussed above frames the document structure. It specifies how to group the messages and in what order they appear. The discourse relationships, such as elaboration, exemplifying, and contrasting, are to be used to make text coherent.

3.2.2. Microplanner and Realiser

The microplanner is concerned with three tasks [14]:

- Lexicalization. Choosing the particular words, syntactic constructs and mark-up annotations used to communicate the information encoded in the document plan.
- Aggregation. Deciding how much information should be communicated in each of the document’s sentences.
- Determining what phrases should be used to identify particular domain entities to the user.

The ontology defines the messages and their sequences of entity nodes, which is used as input for the microplanner. The microplanner completes
its three tasks described above and passes the result for surface realization which takes care of language syntax.

There are two common approaches to plan sentences and lexical choices, entailing the use of a grammar-based or template-based realiser. Since existing grammar-based realisers are so complex that they require a prohibitive amount of time and effort to implement [15], SmartWiki adopts the alternative realiser, a template-based method, for linguistic realisation. A template is a predetermined form that is filled in by information provided at run-time [16]. Although theoretically fixed templates are limited in scenarios than grammar-based realisation, they have an important practical advantage, in that generation is much faster because the size and number of structures to be traversed is relatively small [16, 17].

SmartWiki could design its own templates in the summary board from lexical choice to sentence frames. However, there are already available ontology resources for templates, such as FrameNet [18].

The FrameNet project is building a lexical database of English based on annotating examples of how words are used in actual texts. FrameNet is based on a theory of meaning called Frame Semantics [19, 20, 21]. The basic idea is straightforward: that the meanings of most words can best be understood on the basis of a semantic frame: a description of a type of event, relation, or entity and the participants in it. A frame, according to Fillmore’s frame semantics, describes the meaning of lexical units with reference to a structured background that motivates the conceptual roles they encode. Conceptual roles are represented with a set of slots called frame elements. A semantic frame carries information about the different syntactic realizations of the frame elements, and about their semantic characteristics. FrameNet annotates lexical units from natural language corpora, which provides more flexibility in forming sentence frames.

SmartWiki leverages FrameNet to generate text. Since the ontology only contains limited types of nodes, it is straightforward to manually select Frames for each node type. The proposed frame selection for each type of node is displayed in Table 1. Each frame involves one or more ontology nodes as lexical units to form a complete sentence.

Existing open-source multilingual natural language generators such as NaturalOWL [22] and ELEON [23] build a bridge from ontology relationships to sentence templates such that ontology nodes and their relationships could be assembled into sentences. To demonstrate the text generation taking place in the Summary Board, we leverage NaturalOWL for our case study.
on African Americans’ role in slavery. We first define each ontology node in NaturalOWL and manually pick up frames from FrameNet as sentence templates. Then we assemble generated texts in the sequence according to the ontology tree. Figure 3 shows an example of the resultant text.

3.3. User Interface Design Regarding to Information Extraction

As long as accurate information is available in the ontology, NLG is able to generate readable text for the summary board. This prerequisite of accurate information further depends on accurate information extraction from editor’s input. Due to the fact that Natural Language Understanding (NLU) is still a barrier from experimental research to realistic application, SmartWiki requires editors to explicitly annotate viewpoints with which they agree/disagree in order to manifest their standpoints and provide evidences with necessary references. Thus, capitalizing on this metadata, the implementation correctly annotates these pieces of information based on the ontology. Figure 3 displays a simplified demo for the interface of initiating a dispute in the summary board. Editing an existing dispute shares a similar interface.

The interface does not substantially increase the burden of contribution effort for the editors, since it merely requires the editor to separate content into different edit boxes with computer-interpretable labels. This small ad-

<table>
<thead>
<tr>
<th>Node</th>
<th>Attribute</th>
<th>Frame</th>
<th>Lexical Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dispute</td>
<td>brief</td>
<td>Quarreling</td>
<td>argue, dispute, fight, quarrel,...</td>
</tr>
<tr>
<td>Proponents #</td>
<td>Include</td>
<td>contain, include, have, ...</td>
<td></td>
</tr>
<tr>
<td>Opponents #</td>
<td>Include</td>
<td>contain, include, have,...</td>
<td></td>
</tr>
<tr>
<td>Proponent</td>
<td>social context</td>
<td>People</td>
<td>gentleman, lady, man, woman, people, person,...</td>
</tr>
<tr>
<td>Evidence (by proponent)</td>
<td>Content</td>
<td>Evidence</td>
<td>argue, confirm, corroborate, demonstrate, ...</td>
</tr>
<tr>
<td>Opponent</td>
<td>social context</td>
<td>People</td>
<td>gentleman, lady, man, woman, people, person,...</td>
</tr>
<tr>
<td>Evidence (by opponent)</td>
<td>Content</td>
<td>Evidence</td>
<td>argue, contradict, disprove, demonstrate, ...</td>
</tr>
</tbody>
</table>

Table 1: The Frame Decision For Each Ontology Node
[Disputes] Ending the Slavery Blaming Game
This article contains 5 disputes. 3 of them are heated discussions.

Dispute No.1
There are 8 consenters and 15 opponents arguing about "The sad truth is that without complex business partnerships between African elites and European traders and commercial agents, the slave trade to the New World would have been impossible, at least on the scale it occurred."

Click to view source text (Apr 20, 2012)

Consenters: Henry Gates, Chauncey De Vega, Les Kinsolving, ...

Henry Gates is a professor of Harvard University. He was brought up in West Virginia. ...
Your social similarity with him is 0.32.
He provides the evidence based on the Trans-Atlantic Slave Trade Database. The evidence confirms that we now know the ports from which more than 450,000 of our African ancestors were shipped out to what is now the United States. Through the work of Professors Thornton and Heywood, we also know that the victims of the slave trade were predominantly members of as few as 50 ethnic groups. This data, along with the tracing of blacks’ ancestry through DNA tests, is giving us a fuller understanding of the identities of both the victims and the facilitators of the African slave trade.

Chauncey De Vega is ...

Opponents: Kwabena Akurang-Parry, Ayotunde-Real, Paul I. Aduje, ...

Kwabena Akurang-Parry is a professor of history at Slippenburg University in Pennsylvania. ...
Your social similarity with him is 0.41.
He argues that The viewpoint that “Africans” enslaved “Africans” is obfuscating if not troubling. The deployment of “African” in African history tends to coalesce into obscurantist constructions of identities that allow scholars, for instance, to subtly call into question the humanity of “all” Africans. ...

Ayotunde-Real is ...

Your opinion on the dispute: [ ] Agree [ ] Disagree

Argument:

Evidence:

Reference:

Submit

Dispute No.2
8 consenters and 15 disenters disagree on "Advocates of reparations for the descendants of those slaves generally ignore this unjust problem of the significant role that Africans played in the trade."

Figure 3: An Demo of the Summary Board Demo on A Controversial Article
itional step not only helps NLG processes, but also helps editors organize the content they are contributing.

In the future, when automatic annotation techniques advance to the point where computers are better able to derive meaning from natural language content, this additional step could be omitted and allow editors to input natural language without special tagging.

4. Experiments

Evaluating the knowledge representation for value adherents is much more difficult than evaluating the knowledge representation for truth diggers, because the adapted article version for value adherents requires accurate discernment of compatible editors, which is implicit to the system, while the summary board approach for truth diggers explicitly obtains this from editors at the time of content contribution. Therefore, in this section our experiments focus on the evaluation of editor clustering. The goal of these experiments is to determine whether consensus is obvious within a cluster, while divergence is significant across clusters. We defer discussion of the general system evaluation to section 5.

Our experiment cannot leverage Wikipedia data since it currently contains little social context, lacks reader information, and semantic content is locked away in natural language. Implementing SmartWiki on the web and accumulating users would be a prolonged process. We circumvent these issues of practicality by adopting two popular evaluation approaches: case study and simulation.

Three kinds of information are needed to complete the experiments and evaluation:

- The social background information of Wiki users, such as nationality, education, profession and recognized communities.

- The feedback (e.g., positive/negative) among users on each other’s modification(s).

- The attitudes (e.g. positive/negative) of each editor denoting his/her stance on the topic, which is used as ground truth to evaluate the clustering result.

In our previous paper [24], we only applied the case study approach to evaluate editor clustering. We chose two cases randomly from among Wikipedia’s
list of controversial articles\(^5\) (specifically, “Net Neutrality” and “Smoking”), and another from the heated discussions surrounding a controversial article featured in the New York Times on the historical role of Africans in slavery. Since the data sources of the experiments are not identical, we collected the above information in different ways for Wikipedia articles (Net Neutrality and Smoking) and the New York Times article. Detailed data collection approaches may therefore be found in that previous paper.

In this paper, we extend the experiments with a simulation approach. Our simulation is dedicated to two topics, “divorce” and “alcohol abuse”. Its assumptions are grounded on the previous research \([25, 26, 27]\) and government reports\(^6, 7, 8, 9\). These references cover the attitudes toward the two topics based on three social background attributes, geography, occupation and education.

To construct the background network, only two values are selected in each background attribute for simplicity. Geography contains “Washington” (WA) and “Nevada” (NV), Occupation contains “Dancer&Choreographers” (D&C) and “healthcare practitioner&technical occupations” (H&T), and education contains “high school dropout or lower” (High-) and “high school degree and above” (High+). Then, we generate 30 nodes representing 30 editors. For each node, we randomly assign one of the two attribute values with the same probability (0.5 for each value). This then allows the construction of the background network as described in section 2.1.

To simulate attitudes on each topic reasonably, we calculate the ratio of background attribute values as the likelihood ratio of agreement to the topic based on our investigation. Table 2 shows the ratio of attribute values, attitudes and classification error on each topic. The ratio of each attribute is calculated by firstly calculating statistics against each attribute value. Taking the geography attribute on Divorce as an example, we first calculate the statistics “divorced/(divorced+married)” for Washington and Nevada indi-

\(^6\)http://www.cdc.gov/nchs/data/nvss/marriage_rates_90_95_99-10.pdf by Centers for Disease Control and Prevention
\(^7\)http://www.cdc.gov/nchs/data/nvss/divorce_rates_90_95_99-10.pdf by Centers for Disease Control and Prevention
\(^8\)http://www.cdc.gov/ncbddd/fasd/monitor_table.html by Centers for Disease Control and Prevention
vidually. Then we compare the two statistics and obtain the ratio 3.78:1 as shown in Table 2, where attitudes within each attribute are based on the likelihood of the attribute values. Based on this simulation, people from Washington are deemed positive on Divorce while those from Nevada are deemed negative. We simulate an editor’s final attitude on a topic based on the voting of his/her three background attributes. For example, if an editor is a dancer(+) from Nevada(-) with high school or higher degree(+), his/her attitude to divorce is overall positive. All 30 nodes’ attitudes are generated in this way for the two topics and are used as ground truth for evaluation.

<table>
<thead>
<tr>
<th>Divorce</th>
<th>Geography</th>
<th>Occupation</th>
<th>Education</th>
</tr>
</thead>
<tbody>
<tr>
<td>Statistics</td>
<td>WA : NV</td>
<td>D&amp;C : H&amp;T</td>
<td>High+ : High-</td>
</tr>
<tr>
<td></td>
<td>3.78 : 1</td>
<td>3.23 : 1</td>
<td>1 : 0.82</td>
</tr>
<tr>
<td>Attitude</td>
<td>+ : -</td>
<td>+ : -</td>
<td>+ : -</td>
</tr>
<tr>
<td>Classification Error</td>
<td>0.21</td>
<td>0.24</td>
<td>0.45</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Alcohol</th>
<th>Geography</th>
<th>Occupation</th>
<th>Education</th>
</tr>
</thead>
<tbody>
<tr>
<td>Statistics</td>
<td>WA : NV</td>
<td>D&amp;C : H&amp;T</td>
<td>High+ : High-</td>
</tr>
<tr>
<td></td>
<td>55.2 : 54.8</td>
<td>7.5 : 3.9</td>
<td>1 : 6.34</td>
</tr>
<tr>
<td>Attitude</td>
<td>+ : -</td>
<td>+ : -</td>
<td>- : +</td>
</tr>
<tr>
<td>Classification Error</td>
<td>0.49</td>
<td>0.34</td>
<td>0.14</td>
</tr>
</tbody>
</table>

Table 2: The Frame Decision For Each Ontology Node

To construct the corresponding trust network, we first randomly select 100 directional relationships on the graph. For each directional relationship $node_i \rightarrow node_j$, we produce three feedbacks with each attribute deciding one feedback. We assume that $node_i$ may support $node_j$ if the attribute’s values $a_i$ and $a_j$ agree. We inject randomness into this feedback production step to avoid overfitting by first generating a random value $v \in [0, 1]$. Then, $v$ is compared with classification errors $ce$ of the attribute. The simulated feedback is then determined by the following:

- If $v > ce$ and $a_i = a_j$, feedback is positive
- If $v > ce$ and $a_i \neq a_j$, feedback is negative
- If $v \leq ce$ and $a_i = a_j$, feedback is negative
- If $v \leq ce$ and $a_i \neq a_j$, feedback is positive

23
The process is repeated for all three attributes. In total, three feedbacks are generated for each selected directional relationship. After the above steps, we construct both background network and trust network, and determine the attitudes in the simulation.

Performing the same network construction process on both the case studies and simulation experiments yields clusters which are then evaluated. The same evaluation process performs on both case study experiments and simulation experiments. Figure 4 shows the number of editors aggregated by the resulting attitude determinations.

Observing two distinct camps, we clustered the editors into two groups. In order to get a clear idea of the effectiveness of our components, namely the trust network, background network and the combined social similarity network, we performed spectral clustering separately on the three different network types.

Since the Jaccard Index [28] has been commonly used to assess the similarity between different partitions of the same dataset, we evaluated clustering accuracies using the Jaccard Index calculated between our ground-truthed labeled groups and the clustering results for each network type. The level of agreement between a set of class labels $P$ and a clustering result $Q$ is determined by the number of pairs of points assigned to the same cluster in both partitions as in Equation 12:

$$J(P, Q) = \frac{a}{a + b + c} \tag{12}$$
where \( a \) denotes the number of pairs of points with the same label in \( P \) and assigned to the same cluster in \( Q \), \( b \) denotes the number of pairs with the same label but in different clusters and \( c \) denotes the number of pairs in the same cluster but with different class labels. The Jaccard Index produces a result in the range \([0,1]\), where a value of 1.0 indicates that \( C \) and \( K \) are identical.

Figure 5 shows the performance of the SmartWiki clustering algorithm on the five experiments. Three important conclusions can be derived from the Jaccard Index result.

First, social background and trust relationships do not have equal importance with respect to different topics. In the “slavery” example, the trust network wields significantly more influence on reader compatibility than the background network. This is because the editors in the “slavery” case study wrote comments explicitly agreeing with or opposing one another, and their remarks made explicit their attitudes towards the topic. However, in the “divorce” example, the influence of the background network dominates the influence of the trust network. In the “alcohol” example, the trust and background networks work in concert to improve clustering. Similar to “divorce”, the trust network does not contribute to the clustering in “network neutrality” and “smoking”. We believe this is because the real-content-driven trust model [29] used in Wikipedia related experiments is too limited to deduce an editor’s attitude toward the corresponding topic and the comments from other editors.

Second, the importance of different social background attributes varies according to different topics. In the “alcohol” experiment, if we only choose “occupation” and “education”, the attributes having higher statistical ratios. The Jaccard Index generated by the background network after repeating the same experiment process is 0.55, much higher than 0.36 which is achieved by taking into account all attributes. In the “slavery” topic experiment, if we only use the ethnicity category (black/non-black) to construct the background network, the Jaccard Index produced by this background network is 0.45, which offers more consistency than the 0.37 index achieved when considering all background categories equally. Thus, with respect to different topics, not all background attributes are equally influential. The weight applied to each category when calculating background similarity must therefore be learned from using statistical methods like regression with a sufficient quantity of training samples.

Finally, the social similarity networks do not consistently outperform the
component (trust and background) networks. As a consequence, the combination of trust and background networks produce better results only when both component networks are built on accurate social and biographical information.

The experimental results demonstrate that the SmartWiki model is effective for separate editors of disputes on controversial subjects if provided with appropriate background information and a sufficient trust network. It is also noteworthy that the clustering result is useful not only for discerning compatible knowledge for value adherents, but also for ranking editors of pro and con opinions in the summary board for truth diggers.

5. Further Discussion

5.1. The System Evaluation Metrics

5.1.1. Evaluating the Quality of Knowledge Representation for Value Adherents

The quality of the knowledge representation for value adherents are mainly based on the editor partitioning. There are two evaluations which need to be quantified from the social context perspective. The first is the quality of the editor partition. The second is the association of readers with their most trusted editor cluster.

As mentioned in Section 2.3, the knowledge representation for value adherents consists of paragraphs voted on by all article editors. Without loss
of generality, assume that there are only two clusters generated after editor partitioning. Let us use $M$ as the number of the editors who edited the article and also voted for the $i_{th}$ paragraph presented to the reader, $M_1$ and $M_2$ as the number of editors belonging to the two clusters. As with Equation 13, we use Jaccard Index to evaluate the partitioning as follows:

$$J_i = \frac{\binom{M_1}{2} + \binom{M_2}{2}}{\binom{M_1}{2} + \binom{M_2}{2} + M_1 \times M_2}$$  \hspace{1cm} (13)$$

Hence, the evaluation of the whole article is the average of all $n$ paragraphs’ Jaccard Indexes, as shown in Equation 14:

$$J = \frac{1}{n} \sum J_i$$  \hspace{1cm} (14)$$

The higher $J$ is, the better the partitioning.

Entropy serves as a quantification of uncertainty, and may also be used to evaluate the editor partitioning. Suppose the cluster number is $k$, the $j_{th}$ cluster contains $M_j$ editors. The entropy of the $i_{th}$ paragraph can be acquired in Equation 15:

$$E_i = -\sum_{j=1}^{k} \frac{M_j}{n} \log \frac{M_j}{n}$$  \hspace{1cm} (15)$$

The evaluation of the whole article is therefore the average of all $n$ paragraphs’ entropy, as shown in Equation 16:

$$E = \frac{1}{n} \sum E_i$$  \hspace{1cm} (16)$$

Unlike Jaccard Index, the lower $E$ is, the better the partitioning.

Recall that the association of readers with a trusted editor cluster is based in part on readers’ feedback. Suppose a reader’s feedback could be positive(1) or negative(−1) for each paragraph. Let us use $L$ as the total number of controversial paragraphs and $f_i$ as the feedback on the $i_{th}$ paragraph by the reader $r$. The overall association quality of the whole article may be weighted by the Jaccard Index $J_i$ as demonstrated in Equation 17:

$$AQ = \frac{1}{L} \sum_{i=1}^{L} f_i \times J_i$$  \hspace{1cm} (17)$$
\( AQ \) ranges between \([-1, 1]\) indicating association quality from poorest to the best. The association quality reflects the importance of social context on the preference of a reader. The reason to use the Jaccard Index for weighting is because the more separable the editor clusters are partitioned, the more important the reader’s feedback is for driving the social context model construction.

5.1.2. Evaluating the Quality of the Knowledge Representation for Truth Diggers

The quality of the knowledge representation for truth diggers is quite subjective. Standpoints and evidence of editors explicitly are expressed here and are accessible to all truth diggers. The quality of this type knowledge representation mainly involves the coherence and readability of automatically-generated text. It is therefore harder to quantify the quality of one summary board for all readers.

However, feedback provided by editors and readers yields useful information for evaluation purposes. Editors’ feedbacks manifest their standpoints which can be used to determine the quality of the clustering result used for the knowledge representation for value adherents. These feedbacks may further be used to tell what social factors drive the standpoints of editors. By collecting a sufficient quantity of feedbacks for a group of Wiki articles, supervised machine learning methods like classification could be employed for quantifying the importance of different social factors with respect to certain topics. Similarly, reader feedbacks may indicate their preference for certain editor contributions, allowing trust values between readers and editors to be computed.

5.2. Applicability of SmartWiki to other Wiki Problems

The effectiveness of SmartWiki is not limited to conflict problems. Two other concerns, vandalism and minority opinion suppression, also benefit from the SmartWiki model. A 2007 peer-reviewed study [30] that measured the actual number of page views with damaged content concluded that 42% of damage is repaired almost immediately, i.e., before it can confuse, offend, or mislead readers. Nonetheless, given Wikipedia’s popularity, this leaves hundreds of millions of damaged views. With SmartWiki, vandals are clustered and thereby only influence readers socially close to them. Individual vandals may be mingled with trusted editors, but their identities can be easily revealed since SmartWiki maintains a social context state. That is, their
trust values with respect to other users can be decreased quickly by negative feedback events from readers. As a result, the influence of vandalism is diminished in SmartWiki.

Minority opinion suppression in Wikipedia is another problem which is paid little attention. With an open editing model, the Wiki articles mostly reflect the viewpoints of the majority of editors, though the truth may instead stand with the minority. Previous research [31, 32, 33] has manifested the influence power of minority group in social influence. However, in current Wiki systems, minority opinion is easily removed when these opinions are not tolerated by the majority. Without a fair channel to spread their viewpoints, it is unrealistic to share these opinions, truthful or not. SmartWiki provides a chance for the minority to be heard by allowing the user to adjust parameters that influence other readers socially close to them. When open-minded readers, who are not close to the minority, adjust their social parameters towards the minority editor cluster, it increases the likelihood for others who are similar to such open minded readers to also view these contributions, thus spreading the influence of the minority.

5.3. Concerns About Knowledge Personalization and Privacy Disclosure

The most popular historical trusted article and the summary board are both forms of personalized knowledge presentation based on readers’ social context. Personalization of knowledge presentation has been widely used to filter information on the web to accommodate individual preferences by Google and Yahoo in search engine result rankings. Whereas traditional Wiki systems present predetermined knowledge to all readers, SmartWiki provides readers with the compatible information personalized by their social context. Moreover, we can even extend this approach to the customization by allowing readers of such content to manipulate social parameters (when calculating editor clusters). For example, an advanced SmartWiki reader could enhance the weight of nationality when computing the most trustworthy editor group, which then adjusts the prioritization of the content being presented.

Another potential concern is that providing personalization increases the risk of reinforcing biases. However, personalized systems are able to easily remove personalization and provide universal service by using reasonable defaults. For SmartWiki, the depersonalized knowledge representation is constructed by considering the most viewpoints contributed by globally reputable editors.
Other concerns involve privacy disclosure because SmartWiki relies upon personal information. Preserving privacy requires advanced technology, meticulous system design, responsible service providers, amendatory laws, and privacy-aware users. From a purely technology perspective, much effort has been expended to address privacy disclosure issues. For example, homomorphic encryption [34] has been used to perform computations on proxy data, protecting the actual real data from being exposed to the system performing the computation. Graph anonymization [35] is also applicable in the case of SmartWiki in that similar techniques could be used to partition editors without exposing actual editor backgrounds. Aggregation may also be used to first group similar editors without respect to articles to obscure personal details. These privacy preserving techniques and computer security techniques are an implementation concern for deploying SmartWiki online.

6. Related Work

6.1. Consensus Problem

The consensus problem has a long history in computer science and forms the foundation of the field of distributed computing [36]. In networks of agents (or dynamic systems), “consensus” involves reaching an agreement regarding a certain quantity of interest that depends on the state of all agents. Formal study of consensus problems in groups of experts originated in management science and statistics in the 1960s (See DeGroot [37] and references therein). The theoretical framework for posing and solving consensus problems for networked dynamic systems was introduced by Olfati-Saber and Murray [38, 39] which builds on the earlier work of Fax and Murray [40, 41]. The reason that the conflict problem in Wikipedia is not strictly a consensus problem is that consensus problems assume each individual cannot obtain any benefit without achieving agreement, which is not the case in Wikipedia.

6.2. Conflict and Coordination in Wikipedia

Some research efforts [6, 7, 8] have delved into the conflict and coordination problems in Wikipedia. As briefly mentioned in Section 1, their efforts focus on analyzing and visualizing the conflict patterns rather than fixing the problem for readers. Viégas [6] introduced a new visualization tool to reveal collaboration patterns within the Wiki context. Kittur’s earlier work [7] examined the research on conflict problem and described the development of tools to characterize conflict and coordination costs in Wikipedia. His later
work [8] introduced a mapping technique that takes advantage of socially-annotated hierarchical categories while dealing with the inconsistencies and noise inherent in the distributed way that they are generated.

The key difference between the previous research and our work is that we focus on resolving the conflict problem for the reader and thereby reinforce the NPOV policy, rather than focusing on understanding the conflict patterns themselves.

6.3. Trust in Knowledge Presentation and Perception

The importance of a speaker’s credibility has been studied in epistemology from ancient times. In Aristotle’s systematization of rhetoric [42], a public speaker’s character and credibility to the audience in a discourse is mentioned as “ethos”, which can influence an audience to consider the speaker to be believable. Recent rhetoric scholars [43] regard ethos as “source credibility” and suggested three dimensions for the credibility construct: expertness, trustworthiness and intention toward the receiver.

The concern of content accuracy in Wikipedia arises because ethos of editors are not disclosed. Several trust and reputation models have been proposed to discover reliable editors. Adler et al. [29] proposed a content-driven reputation system for Wikipedia authors where authors gain reputation when their edits are preserved by subsequent authors, and lose reputation when their edits are reverted. Thus, author reputation in their view is based on content evolution only and user-to-user comments or ratings are not used. In our previous research, SocialWiki [9], we described a prototype Wiki system which leverages the power of social networks to automatically manage reputation and trust for Wiki users in terms of the content they contribute and the ratings they receive. We extend this work to also address bias in contributions by leveraging social context as a proxy for user attitudes on controversial topics, and then use this information to generate personalized content for each reader.

7. Conclusion and Future Work

An open Wiki system often involves the concern of content reliability. The approaches in current Wiki systems aiming at eliminating “unreliable” information without regarding to the psychological diversity of readers are impractical for controversial topics. The system design of these Wiki systems
is insufficient to represent appropriate information reflecting different readers’ needs.

In this paper, we presented a new Wiki system, SmartWiki, which provides two novel knowledge representation models to meet the needs of two types of Wiki readers, “value adherents” and “truth diggers”. SmartWiki tracks social context among contributors, inferring affinity relationships between contributors based on their modifications to articles and their biographical similarity with others. For a “value adherent”, SmartWiki discerns the closest editor cluster and produces an article compatible to his/her values. For a “truth digger”, SmartWiki preserves contributed knowledge in a semantic knowledge store and generates a “summary board” which clearly organizes and ranks conflicting viewpoints. Experiments and system analysis shows that our model, SmartWiki, has great potential for revealing editors’ social factors, providing credible knowledge, balancing conflicting viewpoints, avoiding minority opinion suppression and mitigating vandalism.

In our future work, we are interested in the implementation of SmartWiki model as a Facebook application to provide more accurate social context for readers and contributors, as well as to provide a means of authenticated feedback on revisions. In concert with this, we would like to integrate the WYSIWYM [44] methodology in order to allow contributors to input knowledge facts in a fine-grained form directly into the knowledge base while simultaneously being able to read the natural language text that will be generated by those facts, given the ontology of our system. Meanwhile, we will study different methods to construct social graphs for clustering and test their effectiveness in clustering. We hope we can collect enough users to evaluate our solution, but large scale simulations will also be carried out first to obtain a rough idea of the practical feasibility at scale. We are also interested in applying SmartWiki model to other types of knowledge presentation applications, such as Q&A systems (e.g., Yahoo!Answers) and other collaboratively created knowledge repositories.

8. Acknowledgment

We thank the anonymous reviewers for their insightful comments. This work was supported by the United States National Science Foundation FIND (Future Internet Design) program under Grant No. 0832202, GENI, MURI under ARO (Army Research Office), and was sponsored by the Army Re-
search Laboratory and was accomplished under Cooperative Agreement Number W911NF-09-2-0053.

References


