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Reputation Systems of Online Communities Establishing a Research Agenda

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Abstract

Although online communities make it possible for a far greater number of participants to interact on the Web, there are challenges in creating mechanisms that reveal reputations for participants. Reputation Systems provide a proxy that establishes trust in e-commerce communities, social communities, and social news communities. There remain questions as to how reputation systems can be more widely used in online communities without damaging user confidence because participants have strong privacy expectations. This paper will review reputation systems in online communities, examine types, properties, and issues of reputation systems, survey the use of social networks and reputation systems in popular online communities, and present a research agenda to address issues of reputation systems.

Keywords
Online community, reputation system, social network

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BACKGROUND

An online community is an electronic community infrastructure that supports groups of individuals to interact and exchange for a common purpose (Wang 2006). As the Web becomes increasingly distributed with content being created on the edge, and large numbers of individuals and organizations involved in authoring and exchanging information, the need for trust mechanisms within online communities that help identify quality information is undeniable.

A reputation system is the primary mechanism used by online communities to collect, distribute, and aggregate feedback about participants' past behavior and help people to decide whom to trust, and to encourage trustworthy behavior. These systems are "poised" to have a wider influence on online behavior and will affect online and offline organizations (Dellarocas 2003). Reputation systems must include equations for calculating reputation, and define attributes that are made visible. Reputation systems are helpful for participants to derive value from commercial transactions involving goods and services (Resnick et al. 2006), to provide ways to filter and rank information content (Zacharia et al.1999), and to share advice, experience, photos, videos and other files (Gleave 2007). "Online reputation mechanisms are large-scale online word-of-mouth communities in which individuals share opinions on a wide range of topics, including companies, products, services, and even world events" (Dellarocas 2003).

Online reputation systems have encountered various problems that seriously influence their usability and effectiveness (Malaga 2003). The growth of the use of social networks in online communities increasingly compounds challenges as to how reputation systems can be used more widely on the Web without damaging user confidence.

Reputation facilitates the identification of quality resources. Search engines have been highly successful in locating content of quality by using PageRank algorithms. Ranking algorithms use the network graph and value pages more highly if they are referenced by other pages (Altman and Tennenholtz 2004). A Network graph is a visualization of the network where nodes are pages and arcs are links between pages. Network graphs can also be used to analyze the behavior of participants in an online community. A social network is a representation of the relationships of participants within a community. In network graphs, nodes represent participants and edges represent the relationships between them. (Pujol 2001).

The visualizations and analysis of both web networks, and social networks are strikingly similar (Kleinberg 2006). In short, there is a convergence of objects, and authors, and the potential to use digital footprints in a variety of new ways. Nodes can be visualized using network graph structures: Roles, relationships, and patterns of behavior for participants can be observed by following threaded discussions (Fisher 2005; Welser et al. 2007; and Zhang et al. 2007). Patterns of activity between members of a social network have been show to have communication patterns that distinguish one group in a larger community from another (Newman et al. 2005). Most importantly, user activity brings structure to the community (Kelly et al. 2006). Research on network graphs established that decentralized routing and search is possible, and is a fundamental concept for peer-to-peer (P2P) networks. By applying social network principles to ranking systems it becomes more difficult to manipulate reputation systems by creating false identities or colluding in groups (Hogg and Adamic 2004).

This paper reviews the status quo of existing reputation systems and describes potential directions for future work. The rest of this paper is organized as follows. First, reputation systems are defined and categorized into centralized reputation systems and distributed systems.

Weakness of reputation systems and possible solutions are discussed. At the end, the paper presents future research possibilities for reputation systems.

REPUTATION SYSTEMS

There are various definitions for reputation and for reputation systems. When reputation applies to people, reputation is another person's story about you (Windley et al. 2007). Reputation can also apply to organizations, and companies. Reputation systems are mechanisms for identifying the reputation of individuals, and organizations. Some P2P reputation systems for file sharing applications attempt to identify harmful or mislabeled resources embedded in music, video or services files. Reputation systems can be classified as centralized or distributed depending on where the reputation metadata is captured and stored. These reputation systems have some common properties and design principles.

The three major properties necessary for reputation systems to function include: i. authenticating the subject is who they claim to be, ii. determining the subject is capable of performing some specific service, and iii. determining if the subject can consistently deliver the desired result (Lin et al. 2005). These properties can be partially derived from online communities' metadata about users, artifacts, and evaluations. User data could contain authentication and identification information. Artifacts can contain a reference to a document, photo, video or other object that is stored electronically on the Web. Evaluations could be stored as rankings or comments. Metadata of an online community also captures links between types of metadata. For instance, authors and creators can be linked to objects. Secondly, reviews and evaluations can also be linked to objects, as well as objects being linked to evaluations. The linking of data in this way can be useful to reveal patterns of behavior in online discussion groups as well as provide demographic information about participants and their product evaluations (Gleave and Smith 2007).

Reputation can be captured with explicit or implicit information. Explicit information is information that is entered in an online system by a user, while implicit information is derived without the user's knowledge. This detail information can then be summarized, and reputation scores that reflect the past behavior of a participant can be computed based on certain modeling equations. Examples of reputation system using this explicit information include formal rating systems, automatic referral systems, collaborative filtering, and feedback-contingent fee systems, etc. Implicit reputation information relates to social network data, how a user travels through a series of web pages, how much time a user spends in an online store, on shopping history, or using transaction history (Jensen et al. 2002). The way to establish reputation in a community using implicit information is to examine the position of each member in the community, evaluate their standing, and use social network principles to calculate a participants reputation (Pugol 2007). The social graph can be used by itself, or can be used in conjunction with ranking information explicitly entered by users.

A number of social communities also have explicit social network data. Social networks such as Facebook, MySpace, Friendster, and LinkedIn have acquired millions of users. Social communities include profiles, and lists of friends, or contacts. Contacts can be entered manually or gathered automatically from email or instant messaging (Hogg and Adamic 2004). Perceptive computer users realize that this information can be mined even if a participant believes that they have deleted the information.

CENTRALIZED REPUTATION SYSTEMS

Centralized reputation systems have a single server that is responsible for storing all reputation information. The storage of data provides a vast repository, and is often unlimited. Reputation systems algorithmically determine how much information is used to calculate reputation scores. A reputation score could be displayed in a number of categories, or as one value. Decisions made about how reputation is calculated, and used on a central system affect barriers to entry, if reputation scores can be manipulated, and if reputation can be used as filtering criteria. The centralized reputation systems reviewed here are collaborative filtering, online ranking, and ballot box ranking, which all capture explicit information.

Collaborative Filtering

Collaborative filtering (CF) makes automatic predictions about interests based on profiles. Profiles are created to define a number of attributes about content, and/or social environment. CF systems are most often designed for customer management and advertising applications that seek to reach target customers likely to purchase a product.

Collaborative filtering provides a way for a user to view items of interest, or rely on opinions of “friends” to find items of interest. For example, MovieLens is a popular movie ranking website that uses CF in an attempt to match a user with a movie that they may be interested in seeing. Identifying content of interest is based on finding other movies that the user has previously enjoyed. The collaborative filtering (CF) approach selects resources based on relationships between participants by using information from friends. Members are more likely to follow the recommendation made if trust is established (Cosley et al. 2006).

Online Ranking

Online ranking and rating systems engage the user community in authoring, reviewing and rating. Ranking systems have become an important way to evaluate quality of transactions for sellers and buyers in commerce exchanges and quality of content in knowledge exchanges (Altman et al. 2005). Commerce rankings show the history of the buyer and seller; these two parties are the only ones involved in rating. In knowledge ratings, anyone with access to post messages can leave feedback. Online communities may have different criteria as to whom is allowed to leave content, and what type of content they are allowed to create. Some communities may only allow members to leave feedback. Some may require a review prior to posting comments and ranking.

The transaction ranking systems used by eBay or Amazon provides a public view of a participants past behavior. This history of transactions is valuable to predict future behavior. A central trusted server gathers transaction information, and calculates participant reputation scores. Both buyers and sellers are ranked through a history of transactions. This information affects decisions people make as to whom they would choose to do business with on the Web. These ranking systems have made it possible for complete strangers in different geographical areas to exchange goods in a way that would never seem possible. Research has shown that the scores are a reliable way to increase the quantity and quality of transactions (Resnick et al. 2006). The public scores and history of behavior provides a proxy that serves as an indicator for trust and is a great success story on the development of trust on the Web.

Ballot Box Communication

Ballot box communication (BBC) is an enumeration mechanism that aggregates individual rankings and offers limited choices of communication to all participating users. BBC simplifies individual preferences and lowers the cost of participation based on the time users need to spend to leave input. This encourages more people to participate. Sites using BBC include Flickr.com, YouTube.com, Digg.com, and del.icio.us. Two patterns that characterize of BBC are the lack of messages, and the detached mode of communication. The goal is to reveal the interests of the mass population and reflect a many-to-one voice (Xia et al. 2007).

Applications that use BBC communication include access statistics, rating/voting, tagging, and searching. Access statistics can be gathered based on popularity by evaluating view rankings, number of visitors, and number of comments. Rating and voting are useful for polls, rating products, and choosing favorites. Tagging can use BBC by generating metadata of content from keywords, and publishing rankings, or search results. Filtering and searching can use results based on other users' searching and feedback.

Strengths and Weaknesses of Collaborative Filtering, Online Ranking, and BBC

The strength of collaborative filtering is the use of opinions of members in a community to identify content of interest. Reputations and recommendations are domain specific. A user in one domain may have a great deal of expertise, but may have very little to contribute in another domain (Zacharia et al.1999). Each community has members that are able to identify sources of knowledge within a particular community. Major weaknesses of a collaborative filtering strategy include the difficulty to model tastes of a given user, the insufficient numbers of users who contribute to some topics, the low level of participation, and a continuous requirement for providing ratings (Cosley et al. 2006).

Numerous knowledge sites also allow reviews, ratings and rankings for information. Many people can author, and many people can use the authored content provided by online communities. Online communities that use peer reviews find it difficult to explicitly review and rank content because it is difficult to recruit and retain enough volunteers (Cosley et al. 2006). Without creating incentives for participation, there may be a freeloader effect. Freeloaders use the site, but do not provide any additional value.

For a centralized online review process, profiles must be created for potential reviewers, and routing strategies must be in place to manage the items that need to be reviewed and approved before they can be formally published on a website. There are no monetary incentive to contribute information in online communities yet contributions by individuals have fueled the growth of quality content to numerous Wikis, bulletin boards, blogs, and forums (Gleave et al. 2007). Automating the review process using semantic text analysis procedures can also generate a ranking based on quality of content. Some communities have no controls on authoring, some require authors to be registered members, and others have centralized authority that controls the content that is displayed.

PEER-TO-PEER REPUTATION SYSTEMS

Early examples of distributed systems included email, instant messaging and newsgroups. Peer-to-peer (P2P) systems are one type of distributed systems. A P2P system has a number of peer nodes that function as both clients and servers to the other nodes in the network. P2P networks are best known for file sharing applications (Table 2.), for examples Napster, Donkey, and Gnutella. P2P networks have been plagued by files containing malicious content that can easily spread trojan horses, and worms along with vidio and music files that are shared, so the need to identify bad content is essential to these networks.

Peer-to-peer reputation systems have developed in environments where a more centralized approach would not work. Some P2P networks have tasks that are centralized, and others have tasks that are distributed. Building a P2P reputation system that is efficient, scalable and secure for 1) trust computation and trust data storage and 2) for dissemination of content poses considerable challenges in a P2P network (Xiong and Liu 2003). Pure P2P systems like Gnutella and Freenet lack centralized servers for reputation. Napster, used a client-server structure for some tasks (e.g. searching) and a peer-to-peer structure for others.

There has been considerable academic interest in developing algorithms for establishing reputation and trust in P2P communities (see Table 1). A variation of a P2P network that captures the connections to people using digital signatures that can be authenticated is called a friend-to-friend (F2F) network Users in a F2F network cannot find out who else is participating beyond their own circle of friends so F2F networks can grow in size without compromising their users' anonymity (Saarinen 2005).

Four common P2P systems with reputation components include Freenet, Gnutella, Kazaa, and FreeHaven (see Table 2.). A reputation system for Gnutella was investigated (Gupta et al. 2003) that implemented a debit-credit reputation computation (DCRC) and credit-only reputation computation (CORC). The DCRC approach credits peer reputation scores for serving content and debits for downloading. A reputation computation agent (RCA) uses a public key based mechanism and updates the peer reputations in a secure, lightweight, and partially distributed manner.

ISSUES WITH REPUTATION SYSTEMS

Online reputations affect behavior of participants in communities and can induce beneficial outcomes fail because participants and operators can manipulate reputation systems, and because some communities are not protected from potential abuses. Common weaknesses of reputation systems using explicitly information include (Resnick et al. 2000): eliciting feedback, pseudonyms lack of portability, and aggregating feedback

First of all, if there are no incentives for creating feedback then many participants fail to leave feedback. Of the ones who do leave feedback, it is difficult to ensure that the participants' reports are honest. On a commerce rating, one party could black mail another and threaten to post negative feedback that is unrelated to actual performance. A group of sellers might plan to collaborate and rate one another positively, and collude against a competitor by providing negative ratings (Resnick 2000). Rankings could be artificially inflated or deflated by the malicious actions of participants. For information sites, providing a rating takes time, and some people do not want to contribute. Most member-maintained communities don't help members find work (Cosley et al. 2006). For example, Slashdot assigns moderation randomly.

Second, many reputation systems have problems due to the use of pseudonyms. People choose pseudonyms at will and can change these names and erase prior history. It is very easy to create a web identity, or multiple web identities. For commerce transactions, lacking a history translates to a lower trust rating because there is nothing to base a prediction of future behavior. Participants that have established a reputation are concerned about their ratings because of the time it takes to build their history. Pseudonyms that do not reveal identity are important for many types of interaction.

Third, reputation accumulated in one community cannot be shared on another site, causing portability problems. Initially Amazon allowed users to import their ratings from eBay, but eBay claimed its user ratings were proprietary so Amazon discontinued this service. The user would need to travel to different sites and then manually compare the rating of the same item.

The fourth problem with online content is aggregating and displaying feedback. Sites have different standards and customers cannot easily compare ratings between different sites because the calculations and time-periods may be different. For example, eBay provides net feedback by calculating all positives and then subtracts all negatives, but Amazon displays an average. Ratings can cover different time frames, and are not consistent. It has been shown that most ratings are positive and that negative ratings do affect sales (Resnick et al. 2006).

Additionally, Malaga (2004) sites some additional problems:

- Calculations that do not accurately reflect reputation
- Starting reputations that are low and are a barrier to entry
- Reputation scores that can not be used to filter or search
- One general reputation score is provided
- Systems often have unlimited memory

Recently, popular social computing sites have made use of social network data for reputation building purpose (see Table 3. and Table 4.). Although in its infancy, the use of social network data in reputation mechanisms may accelerate with modeling of distributed networks using the social graph (Wang et al. 2007). Social networks will be able to capture implicit information. Some social networks may be explicitly available.

Social network data and collaborative filtering data can be combined to create powerful viral marketing systems (Domingos and Richardson 2001). Domingos (2001) minded large collaborative filtering databases for social networks data in order to develop a model for customer network value. Customer network value is the expected profit based on whom the customer influences to purchase a product, as well as the customers those may influence. The customer's ability to influence purchasing through their friends, and in turn thru their friends of their friends had a powerful marketing value.

Ranking systems are less reliable when ballot-stuffing, unfair ratings, or flooding result in biased reputation estimates. Controlled anonymity and cluster filtering are effective mechanisms to deal with these ranking system problems (Dellarocas 2000).

The visibility and use of social network data in online communities may affect user confidence in reputation systems because participants of online communities have high privacy expectations. At present, little explicit information was found that explained if or how social network data is used in online communities.

There are numerous issues with the expansion of social network data in online communities that include:

- Social networks that record information at an arbitrary resolution
- Computer software that trace activities
- Ownership of profile data
- Ownership of social network data
- Use and publication of social network data

RESEARCH AGENDA FOR REPUTATION SYSTEMS

Reputation mechanisms can be improved by 1) eliciting participation, 2) defining incentive mechanism, 3) using ballot box voting, 4) addressing privacy concerns, 5) creating user-friendly computer interfaces 6) social networks. The six areas of study that provide a research agenda for reputation systems are listed.

Eliciting participation in a community is necessary to create information of interest. Communities often have difficulty getting items reviewed, and it is a struggle to match reviewers with items that need to be reviewed. Social research indicates that people will react more favorably when work assigned matches their interests (Cosley et al. 2006). When a reviewer is assigned items that match their interests, more work is completed. Initially, Wikipedia randomly selected articles for reviewers to edit. When tasks were intelligently routed, the number of edits increased by four times (Cosley et al. 2006).

Incentive Systems may encourage online community members to leave feedback, and to truthfully report their opinions (Yu et al. 2000). In the absence of concrete incentives, online community members may fail to provide feedback or provide intentionally or unintentionally untruthful feedback. A number of researchers are working towards developing mechanisms that provide strict incentives to online community members to both participate as well as truthfully report their observations.

Ballot box communication increases participation and efficiency in online communities by allowing participants to rank content on a website (Xia et al. 2007). The lower cost of participation based on the time users need to spend to leave input encourages more people to leave input. Two patterns that characterize BBC are the lack of messages, and the detached mode of communication. User involvement is collective and not individual.

Online social networks raise privacy concerns and allow for possible misuse (Hogg and Adamic 2004). Many online communities have large datasets based on communication where users have strong privacy expectations. Current safeguards based on making node names anonymous are still open to attacks. Active attacks can easily compromise privacy by creating very few additional nodes (Backstorm 2006). Network Data released about online groups create concerns that small random graphs can be identified. A study using LiveJournal showed that you and six of your friends chosen at random could carry out the same attack and compromise 10 users (Backstrorm 2006). Network data needs to address privacy concerns by limiting the amount of the social graph that can be accessed by users. Motivated by issues of privacy, trust, and scalability, some researchers are beginning to look at distributed feedback mechanism architectures (Lowel-Nowell et al. 2005). A Trusted third party could be used to handle the network data and reveal only final reputation scores.

Tools can be developed to create a high quality interactions within an online community and help an online community provide reputable information (Kelly et al. 2002). A well designed computer interface can facilitate the creation of high-quality reputable information by tracking all 1) user activity, communications, and feedback and 2) creating authoring tools and 3) creating a status system for members. Further, this information can be recompiled to improve navigability, content filtering and presentation. A status system helps to encourage participation, and add to the knowledge base. By making the contributions, and ranking of artifacts part of reputation calculations, the community becomes self-monitoring. The integration of metric data into the content and structure of a web site can help solve the problems of bad behavior, lack of participation, and difficulty of finding content.

The use of social network data in reputation systems has been shown to have benefits to reputation systems, and this area presents a new area of study. The growing availability of explicit social network data available on online communities makes it possible to use social network data.

CONCLUSION

Online communities have transformed how we use the Web. There are challenges in modeling social communities and providing technology that supports a shift to distributed computing. Reviewing centralized and distributed P2P reputation systems provides a starting point, and provides a visualization of how reputation systems emerged from a way to rate transactions on eBay to a way to rate content in newsgroups, forums, and knowledge sharing sites. Online communities have various needs, and different types of reputation systems are implemented depending on these needs. Equations and databases used in reputation systems will continue to improve information sharing. The emergence of social networks in online communities mirrors how people interact. Online communities have a network structure because of the behavior of its participants. As more information is available on the Web about social networks, social networks are likely to play an important role in reputation systems.

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Table 1. Infrastructures for P2P Reputation Systems

Name	Reputation System Type	Description
EigenTrust	Distributed-Hash-Table overlay network.	Calculates global peer reputation by considering the entire system's history. Each peer is assigned a global trust value, which reflects the experiences of all the peers in the network with peer. The algorithm aggregates the scores by a weighted sum of all raw reputation scores.
PeerTrust	Fully distributed overlay for trust propagation, public-key infrastructure	A weighted sum of five peer feedback factors peer records scope credibility transaction context Community context prevents peers from taking some malicious abuses.
PowerTrust	Distributed ranking mechanism	Leverages the power-law feedback Characteristics in online reputation like eBay. The PowerTrust system dynamically selects small number of power nodes that are most reputable.
FuzzyTrust	Distributed	Based on fuzzy logic inferences, which can better handle uncertainty, fuzziness, and incomplete information in peer trust reports. This system aggregates peer reputations with affordable message overhead.
Xrep	Distributed polling algorithm	Resource requestors assess the reliability of a resource offered by a participant before initiating the download.
TrustWare	Distributed	Peer trustworthiness derived from long-term reputation evaluation and short-term risk evaluation.

(Damiani 2002 ;Wang et al. 2008;Xiong and Liu 2003).

Table 2. Common P2P Systems with Reputation Component

Name	**System**	**Description**
Freenet	P2P Content Publishing and Storage Systems	Distributed anonymous information storage and retrieval system.
Gnutella	P2P File Exchange Systems	Distributed file sharing—purely decentralized.
Kazaa	P2P File Exchange Systems	Distributed file sharing—partially centralized.
FreeHaven	P2P Content Publishing and Storage Systems	A flexible system for anonymous storage.

(Androutsellis-Theotokis and Spinellis 2004)

Table 3. Reputation Systems in Popular Online Communities

				3 Month Average 1-14-2008 *			OpenID Used	Reputation System	Object Rating	Participant Scores		Level of Participation Supported		
Name of Site	**Description**	**Membership**	**Web Rank ***	**Reach**	**Traffic Rank**	**Views per User**				**Reputation Score**	**Rater Score**	**Comments**	**Ballot Box Ranking**	**Summaries**
eBay	e-commerce		9	2.0%	20	15.1	No	centralized	Yes	Yes	Yes	Yes	No	Yes
Amazon	e-commerce		25	1.8%	31	6.8	No	centralized	Yes Recommender	Yes	Yes	Yes	No	Yes
YouTube	social networking/video		5	18.0%	3	14.5	No	centralized	Yes	No	No	Yes	Yes	No
MySpace	social networking	162,400,000	10	5.6%	6	30.5	No	centralized	Movies, Books, etc.	No	No	No	No	No
Facebook	social networking	52,000,000	24	5.4%	7	30.6	No	centralized	No	No	No	No	No	No
Friendster	social networking	29,000,000	260	1.88%	14	38.2	No	centralized	No	No	No	No	No	No
Blogger	social networking		174	7.35%	12	4.2	Yes	centralized	Yes	No	No	Yes	Yes	No
LinkedIn	social networking	17,000,000	1049	0.33%	205	8.9	No	centralized	No	No	No	No	No	No
Del.icio.us	social book marking		1721	0.3%	391	3.3	No	centralized	Yes	No	No	No	Yes	No
Flickr	yahoo Photo sharing	4,000,000	166	1.5%	37	8.6	No	centralized	Yes	No	No	Yes	Yes	No
StumbleUpon	website reference	4,200,000	992	0.3%	298	5.8	No	centralized	Yes Recommender	No	No	Yes	No	No
Epinions	consumer		1116	0.07%	2185	2.2	No	centralized	Yes	Yes	No	Yes	No	Yes
Wikipedia	reference		13	8.48%	9	5.2	No	centralized	Collaborative Filtering	No	No	Yes	No	No

1. Traffic is measured based on Alexa Toolbar users,
2. Reach is the percent of global internet users who visit this site.
3. Traffic rank is based on a measure of page views, reaches, and is based on the geometric mean averaged over time. Sites are defined on a domain level
4. Page views are the number of unique pages viewed per user per day for the site.

Table 4. OpenID and Profile Information for Communities

		OpenID Used	Information		comment
Name of Site	Description		Profiles	Friends List	
eBay	E-commerce	No	Yes	Yes	
Amazon	E-commerce	No	Yes	Yes	Recommendations
YouTube	Social Networking/Video	No	Yes	Yes	
MySpace	Social Networking	No	Yes	Yes	Interest Groups
Facebook	Social Networking	No	Yes	Yes	
Friendster	Social Networking	No	Yes	Yes	Friends of Friends
Blogger.com	Social Networking	Yes	Yes		
LinkedIn	Social Networking /Business	No	Yes	Yes	
Del.icio.us	Social Bookmarking	No	Yes Knowledge Sharing Social Software System	Yes	Matches users who bookmark the same pages or use the same keywords
Flickr	Photo sharing	No	Yes	Yes	
StumbleUpon	Newsgroup	No	Yes	Yes	Collaborative filtering Peer & Social networking principles. Accumulate Karma Plug-in for web browser
Epinions	Consumer	No	Yes	No	Create Web of Trust, readers rate reviewers, reviewers get paid
Wikipedia.org	Reference	No	Yes	No	SuggestBot Watch list Preferences Contributions Talk