Evaluating Reputation in VGI-enabled Applications

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ABSTRACT

Volunteered Geographic Information (VGI) is an approach to crowdsource information about geospatial objects around us, as implemented in Open Street Map, Google Map Maker and WikiMapia projects. The value of this content has been recognized by both researchers and organizations for acquiring free, timely and detailed spatial data versus standard spatial data warehouses where objects are created by professionals with variable updating time. However, evaluating its quality and handling its heterogeneity remain challenging concerns. For instance, VGI data sources have been compared to authoritative geospatial ones on specific regions/areas in order to determine an average overall quality level. In user-oriented VGI-based applications, it can be more relevant to assess the quality of particular contents, like specific Points of Interest. In this case, evaluation can be performed indirectly by reputation scores associated with the specific content. This paper focuses on this last aspect. Our contribution primarily provides a comprehensive model and architecture for reputation evaluation aimed to assess quality of VGI content. On the other hand, we also focus on applications by discussing two motivating scenarios for reputation-enhanced VGI data in the context of geospatial decision support systems and in recommending tourist itineraries.

Keywords

Reputation Evaluation, Volunteered Geographic Information, e-Tourism, Spatial DSS, User-Generated Content.

1. INTRODUCTION

Following the Web 2.0 trend, more and more content published on the Web is generated by end users. Due to the growing availability of Geographic Positioning System (GPS)-enabled mobile devices, this user-generated content is commonly associated with geographical coordinates. This feature is more and more recognized as relevant by researchers and organizations [14, 11]. Recent platforms, including Open Street Map (OSM) and Wikimapia, permit users to contextualize the content of these maps. These platforms make it easy interacting with the map content through some editing functions, such as add and edit. These activities are known as volunteered geographical information (VGI). VGI could provide more timely, updated and detailed content than authoritative sources. Moreover, unlike commercial geospatial sources, VGI contents have a special value because they are able to capture multiple perspectives of the same location as perceived by different users from different cultural backgrounds (e.g., a Buddhist temple could be depicted as a touristic attraction or a religious location; a street with speed bumps can be a described a potential danger by a motorbike user and as a safe street by a pedestrian one).

The process of VGI generation is intrinsically subjective and loosely controlled; it relies very often on devices having variable level of precision and on untrained volunteers. As a consequence, VGI data are highly heterogeneous in coverage, density and quality. Techniques to estimate and improve the quality of these data are therefore needed [2, 9, 15].

A classification of approaches for assessing the quality of VGI have been discussed in [10]. Other approaches, as in [9], aimed to establish the average quality of VGI data on specific regions/areas by comparing it with authoritative data and measuring the existing discrepancies in terms of standard quality metrics such as completeness, consistency and both positional and temporal accuracy. However, knowing the quality of specific VGI data, like description and location of a specific point of interest (PoI), is more relevant for user-oriented applications focusing on the description of particular geospatial objects. In these cases, there is the need to know whether to trust or not the VGI description. Examples are applications providing information on location of architectural barriers [7] or potability of water wells [3].

Therefore, defining quality indicators for VGI data and, specifically, PoIs is relevant and various ones have been proposed [15]. Indicators focus on aspects influencing the quality without measuring it directly. Some of them are: lineage (which relies on the history and evolution of the dataset describing, for example, a PoI), quality of textual descriptions [4], experience [4], trustworthiness and reputation [8].

In this paper, we provide a contribution to the VGI research which is twofold. Firstly, we discuss two motivating applicative scenarios for reputation-enhanced georeferenced data in the context of geospatial decision support systems and in recommending tourist itineraries. Then, we present and evaluate a comprehensive model and some preliminary experiments for evaluating reputation in user-generated georeferenced data. This contribution extends and refines our previous work [12] by including time and other features in the model. The paper connects its contribution to the challenges arising in linked data management, by leveraging OpenStreet Map, Wikimapia, Panoramio, or Googlemaps datasets. The described approach could be implemented with Linked Data and, as future direction, it can become a use-case for the recent work on Open Annotation[1].

The remainder of this paper is organized as follows. In Section 2, the applicative scenarios are presented to show the potentiality of integrating reputation scores and user-generated georeferenced data in specific applications. Some related work is discussed in Section 3. In Section 4, we present our multi-layer architecture to enhance VGI reputation. In Section 5, the Reputation Model is proposed. The paper concludes in Section 6 with some suggestions for a future model extension and our research roadmap.

2. MOTIVATING SCENARIOS

2.1 VGI in Spatial Decision Support Systems

Spatial Decision Support Systems (SDSSs) are being created to allow several stakeholders to collaboratively plan their actions. In such systems, Spatial Data Warehouses (SDWs) are extensively deployed as common repositories where stakeholders' data sources are integrated and stored [5]. In order to load data into a SDW, a complex Extract-Load-Transform (ETL) process is typically used. Because of the growing complexity in several real-life scenarios, decision-makers are relying more on advanced technologies to collect data anytime, anywhere, about events and objects of interest. As these technologies became widely available as wearable and portable devices (e.g., smartphones), decision-makers are increasingly soliciting individuals to actively report on ongoing events. Several tools are therefore being created to enable VGI datasets to be acquired within the context of SDSSs. The creation of such tools is motivated by the important role of VGI techniques in collecting on-the-fly valuable data, improving the understanding of ongoing events, discovering behavioural patterns that would improve decision-making processes, and implementing proper mechanisms to provide individuals with customized services. Although some progress is being achieved, several obstacles are still challenging the efforts of integrating VGI capabilities within SDWs. For instance, the VGI datasets are commonly unstructured, with varying qualities, formats, and granularities. In order to meet the DW requirements, extensive transformation efforts must be performed prior to sending the VGI datasets to the ETL process. These efforts are supported in our architecture (See Fig. 1) by the Integration Module. Furthermore, since VGI datasets are voluntary collected by experts, non-experts, and even malicious individuals, their values, credibility, veracity, and trustworthiness will be investigated by our Reputation Module. As this investigation is expected to happen frequently, assigning reputation values to VGI participants and contributions is a relevant option. These values are used to prioritize data loading into the SDW and relieve this process from unnecessary costly processing activities.

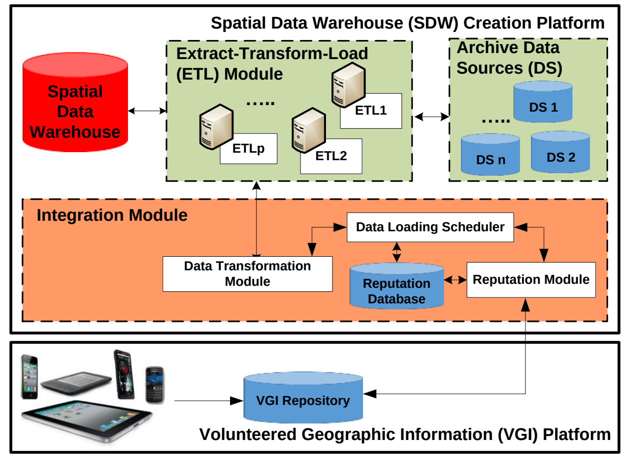

Figure 1: VGI Integration Module in a Spatial DW architecture.

2.2 Recommending sigthseeing tours with Tripbuilder

Tourists approaching their destination for the first time deal with the problem of planning a sightseeing itinerary that covers the most subjectively interesting attractions while fitting the time available for their visit. TripBuilder[2] is an unsupervised system helping tourists to build their own personalized sightseeing tour [6]. Given the target destination, the time available for the visit, and the tourist's profile, TripBuilder recommends a time-budgeted tour that maximizes tourist's interests and takes into account both the time needed to enjoy the attractions and to move from one PoI to the next one. A distinctive feature of TripBuilder is that the knowledge base feeding the recommendation model is entirely and automatically extracted from publicy available crowdsourced data like Flickr[3] and Wikipedia[4].

TripBuilder extracts from Wikipedia the multilingual name of the PoI, its geographic coordinates, the categories of the PoI according to a category. By clustering and spatially matching tourists' photo albums from Flickr on the relevant PoIs extracted from Wikipedia pages, we can thus derive a knowledge base that represents the behavior of people visiting a given city. The Wikipedia categories of the PoIs visited by a given tourist are used to build her profile and to characterize the trajectories across the PoIs.

However, Wikipedia as a source of PoIs for tourism recom-

[1]http://www.openannotation.org/.

[2]http://tripbuilder.isti.cnr.it

[3]http://www.flickr.com

[4]http://www.wikipedia.com

mendations has some limitations. For example, several areas of the world, like latin-america or asian countries, are not covered by a sufficient number of Wikipedia pages describing individual tourist attractions inside a city like museums or monuments. This means that in these areas the PoIs are too sparse to describe itineraries and thus we need to rely on other, possibly local, sources of crowd data. This calls for the integration of local-based, up-to-date, user-generated and reliable Volunteer Geographical data source capable to describe the Points of Interests, crucial for expanding Tripbuilder in these areas. The integration of these data requires a reputation evaluation mechanism to ensure that the user-generated data are reliable enough for recommending tourists.

3. RELATED WORK

Several research and development works have attempted to estimate reputation in VGI applications. For example, Bishr and Khun [3] described a reputation model based on coherence between volunteers' reports on potability of water wells in developing countries. The potability status has only two possible values: good or bad. Time is explicitly included in the model. For instance, trustworthiness in the reports about potability is reduced proportionally to the elapsed time since the creation time of reports. Our model considers more general VGI scenarios allowing for complex descriptions of objects. Another approach is given in Zhao et al. [17]. The approach estimates the trustworthiness of VGI data based on contributor's reputation as well as on analyzing several versions of VGI data. This is similar to the approaches proposed by Keßler et al. [13] and D'Antonio et al. [8]. Each version is created by a contributor and describes the current status of a geospatial object. The level of trust for a specific version depends on: (i) contributor's reputation; (ii) similarity distance between this version and the previous one for the same object; and (iii) level of trust in the previous version. This approach looks actually inspired by D'Antonio et al. [8], but additionally it provides a detailed data model. As per our model, these authors distinguish between implicit and explicit assessment of contributors.

Trustworthiness and reputation have been studied in other contexts, for example crowdsourcing [1] and multi-agent systems [16]. In particular, the work [1] is about trustworthiness of semantic annotations of textual contents. The discussion is interesting because it considers as not avoidable some levels of disagreement in users' annotations for the same text. A particular annotation is considered acceptable when the disagreement with other annotations is not exceeding a given level. In fact, in some cases, this situation reflects the presence of semantic ambiguity in the described object, which can be perceived and annotated by different users according to different points of view.

Our approach aims to provide a comprehensive evaluation model for reputation in VGI. It extends our previous work by including temporal aspects influencing reputation and the asymmetry of feedbacks, as proposed too in [3]. It distinguishes as well between direct and indirect user feedbacks. Another benefit of our contribution is to be resistant to manipulation attempts done by users with a malicious attitude. Some preliminary experimentation provides encouraging results in this direction.

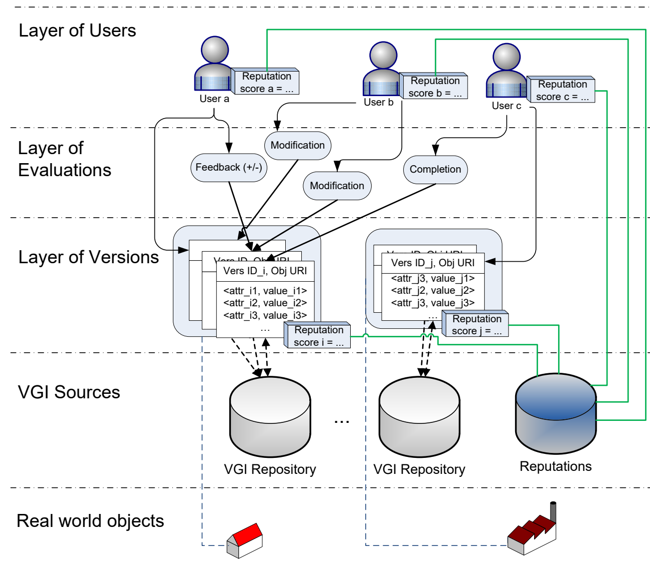

Figure 2: Reference multi-layer architecture.

4. AN ARCHITECTURE FOR REPUTATION ENHANCED-VGI

In this section, we present a multi-layer architecture (see Fig. 2) for VGI enhanced with reputation scores. This architecture briefly introduces the main concepts of our model for reputation evaluation. Main focus of this paper is the layer of evaluations and, secondly, the layer of versions. According to [17] a VGI *version* is the description of a state of a geospatial real world object at a certain time and authored by a user. For the same state more versions can be produced, as well as the state of an object can change during the object lifespan (e.g., its address can change) making out of date previous versions describing it. We model a version (e.g., the description of a georeferenced PoI or a element on a map, as a street) as set of pairs $< attribute, value >$ with a URI identifying the described object and can be completed or modified many times. Versions are stored in VGI repositories, like OSM and WikiMapia. In order to improve an existing version, a user shall modify or complete it to originate another version for the same object. In Fig. 2, versions stored in the same repository and describing the status of an object are grouped together. A user can also give a direct feedback, positive or a negative, to versions in order to express agreement or disagreement on the content.

We consider four user activities as below: A user can: (i) create a new version, (ii) modify an existing version, (iii) complete an existing version, or (iv) give a direct feedback to a version.

A completion is a set of pairs $< attribute, value >$ added to an existing version (e.g., adding <phone2, +39303333020> to the version). A modification consists of new values for pairs $< attribute, value >$ already existing in the version (e.g., the pair <opening, Monday-Friday> corrects <opening, Monday-Saturday>). Every time a user makes a modification (respectively, a completion) to a version A, a new version *A'* is generated from A by substituting the original with the modified content (respectively, by adding content). For each version (e.g., A, *A'*), its creation time is stored with the version. A reputation value in $[0, 1]$ is associated with each user and each version. Modifications, completions and direct feedbacks on A modify both the reputations of the version A and of the author of A. In Fig. 2, reputation scores of authors and versions are stored and managed by a separated platform from the VGI source repositories.

5. REPUTATION EVALUATION MODEL

In this section, we describe some requirements we adopted for reputation evaluation and we provide the metrics. Our purpose is to formalize an evaluation model based on our multi-layer architecture by taking into account a set of requirements we consider important for quantifying reputation. According to the architecture in Fig. 2, presented in the previous section, a user can perform activities to produce georeferenced content (i.e., versions) and to evaluate other peers' content. In our approach, these activities are subject to constraints. For example, a user is not allowed to give directly a feedback to another user and he cannot evaluate more than once a version. This is set in order to prohibit a malicious user from deliberately increasing reputation of other specific peers or their contents. Reputation of versions does not depend only on feedbacks, considered as direct evaluations, but also on modifications and completions, which we consider kind of indirect feedbacks. In fact, we assume that a modification reduces the reputation because the user producing it considers the original version as including errors or requiring updates. On the contrary, a user making a completion to a version recognizes it as correct, but incomplete. Therefore, a completion activity has to increase the reputation of the original version.
In the following, we formalize the metrics.

User reputation.

Every time a feedback, completion or modification are made on a version, the *User reputation* score of its author is updated as follows:

$$uR_u = \begin{cases} uR_0 \\ (1-e^{-n}) \cdot \frac{POS_u}{POS_u+NEG_u} + e^{-n} \cdot uR_0 \end{cases} \tag{1}$$

where $uR_u \in [0,1]$. The first case of Eq. (1) applies when no activities have been made yet to any versions authored by user u, i.e., $POS_u = 0$ and $NEG_u = 0$. The term uR_0 is the initial user reputation, usually set to a low value (e.g., 0.3) equal for every user. Alternatively, this value could be set proportionally to the completeness in filling the user registration profile. In the second case of Eq. (1), parameter n is the total number of versions produced by user u. This includes new versions and versions produced due to the modifications or completions of other versions. The role of coefficient e^{-n} is to reduce the amplitude of the initial oscillations of the uR_u value when n is low (e.g., $n < 3$). This avoids that a single positive or negative feedback can increase or decrease considerably the reputation uR_u when a user has produced only few versions. Moreover, as n increases the initial reputation uR_0 counts less and the user reputation score depends more on the feedbacks provided by other users.
Definition of terms POS_u and NEG_u are as below:

$$POS_u = \sum_{v \in V(u)} POS_v \cdot h(t_v) \qquad NEG_u = \sum_{v \in V(u)} NEG_v \cdot h(t_v) \tag{2}$$

where $V(u)$ is the set of contributions produced by u and v is one version. POS_c and NEG_c are terms defined in the following and summarizing, respectively, positive and negative feedbacks expressed on v. $h(t_v)$ is a coefficient weighting the contribution of POS_v and NEG_v and depends on the creation time t_v of v.

Aging of versions.

The coefficient $h()$ assigns a higher weight to feedbacks expressed on recent versions. Its value decreases linearly with the difference between the time t, when the POS_u and NEG_u expressions are evaluated, and the creation time t_v of version v. In particular, $h(t_v)$ is equal to 0 when this difference is larger than value α. For example, in our experiments we have chosen α equivalent to 180 days so the feedbacks on a version are no more changing the author's reputation when the version is older than 180 days. This coefficient is defined as:

$$h(t_c) = \begin{cases} \frac{\alpha-(t-t_v)}{\alpha} & \text{if } t - t_v < \alpha \\ 0 & \text{if } t - t_v \geq \alpha \end{cases} \tag{3}$$

where $h(t_c) \in [0,1]$. Because POS_v and NEG_v are always positive then POS_u and NEG_u are positive as well.

Reputation of versions.

The reputation score vR_v of a version v is based on (implicit and explicit) feedbacks given to v by other peers.

$$vR_v = \begin{cases} vR_0 \\ (1-e^{-k}) \cdot \frac{POS_v}{POS_v+NEG_v} + e^{-k} \cdot vR_0 \end{cases} \tag{4}$$

where $vR_v \in [0,1]$ and k is the number of feedbacks on v. The first case in Eq. (4) applies when $k = 0$. In the second case, when $k \neq 0$, reputation score vR_v is defined according to an expression similar to the one for user reputation score, as in Eq. 1.

The initial reputation $vR_0 \in [0,1]$ depends on the type of activity (new version, modification, completion) to create v and on the reputation of its author u, as follows:

$$vR_0 = \begin{cases} uR_u & \text{if } vers(v) \\ (1 - Sim(v, vPrev)) \cdot uR_u + \\ Sim(v, vPrev) \cdot min(vR_{vPrev}, uR_u) & \text{otherwise} \end{cases} \tag{5}$$

where $vers(v)$ is true when v is a new version and, in this case, the initial reputation vR_0 is set to be equal to the reputation uR_u of the author. Otherwise, vR_0 is a weighted mean of: (i) the author reputation uR_u, and (ii) the minimum between reputation of the parent contribution $vPrev$, which v is obtained from by modification or completion, and uR_u. The rationale for selecting the minimum is the following. If reputation of $vPrev$ is high and uR_u is low, a user u could maliciously modify a version with high reputation in order to produce a version v with some wrong content (e.g., a different web site address) but having initially a high reputation. By taking the minimum, this cannot happen since

Cooperative Users	Correct Identifications (U)
90%	99.80%
70%	99.60%
50%	49.40%

(a)

Cooperative Users	Correct Identifications (V)
90%	99.07%
70%	93.44%
50%	49.80%

(b)

Figure 3: Identification of: (a) users, (b) versions, using the simplified model.

the user reputation uR_u is the upper bound of the initial reputation of v. $Sim(v, vPrev) \in [0, 1]$ is a similarity coefficient between the previous and the current version. More these versions are dissimilar (i.e., $Sim(v, vPrev) \sim 0$), more the reputation score is near to the author's reputation score uR_u and therefore independent of the reputation of $vPrev$. This is because the version v modifies significantly $vPrev$ so the reputation of v should be more focused on the author than on the previous version $vPrev$. We will not detail here how to calculate $Sim(v, vPrev)$. It is proportional to the number of pairs $< attribute, value >$ equal in both the versions v and $vPrev$.

Feedback evaluation.

The values of POS_v and NEG_v, summarizing the positive and negative amount of direct and indirect feedbacks on version v, are updated every time a new feedback on v is produced. The impact of a feedback by a user u_f is proportional to reputation of u_f. In particular, the equation for updating the current POS_v when either a positive feedback or a completion f is submitted by u_f with reputation uR_f, is the following:

$$POS'_v = POS_v + \omega \cdot \begin{cases} uR_f & \text{if } f \text{ is pos. feedback} \\ Sim(v', v) \cdot uR_f & \text{if } f \text{ is completion} \end{cases} \quad (6)$$

In case of completion, v' denotes the upgraded version of v after this operation. More the versions v and v' are similar, higher the increasing of POS_v due to the presence of the similarity coefficient $Sim(v', v)$. The rationale is that if v' is very different from v, it is not considered a completely positive evaluation of v, i.e., v was evaluated as incomplete. In this case, POS'_v has not to differ a lot from POS_v.

We define as well the equation for updating NEG_v when either a negative feedback or a modification f is submitted by u_f with reputation uR_f:

$$NEG'_v = NEG_v + (1-\omega) \cdot \begin{cases} uR_f & \text{if } f \text{ is neg. feedback} \\ (1 - Sim(v', v)) \cdot uR_f & \text{if } f \text{ is modification} \end{cases} \quad (7)$$

Finally, to note that the coefficient $\omega \in [0, 1]$ in Eq. (6) and in Eq. (7) permits to make asymmetric the way POS_c and NEG_c are increased by a certain feedback. By assigning a low value to ω, a negative feedback increases more NEG_v than a positive one does on POS_v. Here we include in the model a notion of asymmetry between positive and negative feedback as Bishr and Khun [3], who observe that negative feedbacks in real life have a stronger absolute impact on reputation than positive ones and therefore should be weighted differently.

Experimental evaluation.

We discuss some preliminary experimental results to test our approach. Even if these experiments are limited the obtained results are encouraging. We implemented the reputation model as described in the previous section and tested its accuracy on a simulated dataset in a Matlab environment.

In our simulation, a user is labeled either cooperative or non-cooperative and versions are labeled either correct (i.e., supposed to represent correctly the reality) or incorrect. During the simulation, cooperative users can: (i) create correct versions, and (ii) perform activities on existing versions that are coherent with their nature; which means if a version they evaluate is correct then they can give either a positive feedback or complete it. Non-cooperative users, instead, behave according to a malicious attitude. They can: (i) create incorrect versions, (ii) give either negative feedbacks or modify correct versions, to reduce the reputations of versions and authors. Moreover, a user can be active by performing any type of action, or non active, by giving direct feedbacks only.

By running some simulations, we measure the accuracy of the reputation model in identifying correctly, i.e., according to the labels, cooperative/non-cooperative users and correct/incorrect versions. We recall that the objective of the proposed reputation model is to assign high reputation scores to cooperative users and to correct versions, or low reputation scores otherwise. At the end of a simulation, a cooperative user is identified correctly if the reputation score is in the interval $[0.5, 1]$; a non-cooperative user is identified correctly if the reputation score is in the interval $[0, 0.5]$. We use the same criteria for identification of versions. In the experiment, we want to observe this phenomenon by varying the number of cooperative users. We also disregard some features like the asymmetry of feedbacks (i.e., we set $\omega = 0.5$) and the aging of versions (i.e., we set $h(t_c) = 1$). The result permits to show good levels of accuracy even in a simplified version of the model. All the numerical results presented in the following are obtained as averages of ten running simulations. We set the percentage of active users to 10%. Therefore, the remaining 90% of users are non active ones. Approximately, this proportion reflects the one between active users, contributing as reviewers, and users giving only feedbacks, with reference to the Amazon community[5]. In our simulations, active users are selected randomly among others. The type of an activity performed during the simulation is chosen randomly based on the probability distribution: *creation of a new version*, 1%; *modification*, 1%; *completion*, 1%; *direct feedback*, 97%. The results concerning the amount of users identified correctly is shown in Fig. 3(a). The result concerning the amount of identified versions is in Fig. 3(b).

We can notice the high identification performances with

[5]https://www.quora.com/What-percentage-of-buyers-write-reviews-on-Amazon

percentages of cooperative users of 90% and 70%. The results are even better if we consider the correct identification of only versions having at least 5 feedbacks, where with 70% of cooperative users, we got 92.2% of correct identifications (not reported in the figure). On the contrary, with only 50% of cooperative users the performances drop down. In this case, the number of cooperative and non-cooperative users are the same and every user has the same initial reputation score uR_0, so the model is not able to identify who is cooperative and who is not.

6. CONCLUSIONS AND PERSPECTIVES

In this work, we discussed a novel comprehensive model and architecture for reputation evaluation of Volunteered Geographic Information content. An initial evaluation based on simulations has been presented, as well. Our approach defines metrics to score a composite reputation of VGI data coming from unknown contributors. We promote the usefulness of our model by discussing the integration of VGI data with reputation scores in two different application scenarios. Future work includes dealing with inconsistency that may arise due to repeated updates and completions for the same PoI. We are also planning to perform a deeper evaluation of the model, studying its possible joint use with other techniques for quality assessment in VGI data, and improving the architecture and the model in order to better integrate them with the discussed applicative scenarios.

7. REFERENCES

[1] Lora Aroyo and Chris Welty. Crowd truth: Harnessing disagreement in crowdsourcing a relation extraction gold standard. *WebSci2013. ACM*, 2013, 2013.

[2] Jamal Jokar Arsanjani, Peter Mooney, Alexander Zipf, and Anne Schauss. Quality assessment of the contributed land use information from openstreetmap versus authoritative datasets. In *OpenStreetMap in GIScience*, pages 37–58. Springer, 2015.

[3] Mohamed Bishr and Werner Kuhn. Trust and reputation models for quality assessment of human sensor observations. In Thora Tenbrink, John Stell, Antony Galton, and Zena Wood, editors, *Spatial Information Theory: 11th International Conference, COSIT 2013, Scarborough, UK, September 2-6, 2013. Proceedings*, pages 53–73. Springer International Publishing, Cham, 2013.

[4] Gloria Bordogna, Paola Carrara, Laura Criscuolo, Monica Pepe, and Anna Rampini. A linguistic decision making approach to assess the quality of volunteer geographic information for citizen science. *Information Sciences*, 258:312 – 327, 2014.

[5] Boubaker Boulekrouche, Nafaâ Jabeur, and Zaia Alimazighi. Toward integrating grid and cloud-based concepts for an enhanced deployment of spatial data warehouses in cyber-physical system applications. *Journal of Ambient Intelligence and Humanized Computing*, 7(4):475–487, 2016.

[6] Igo Ramalho Brilhante, Jose Antonio Macedo, Franco Maria Nardini, Raffaele Perego, and Chiara Renso. On planning sightseeing tours with tripbuilder. *Information Processing & Management*, 51(2):1 – 15, 2015.

[7] Maria Antonia Brovelli, Marco Minghini, and Giorgio Zamboni. Public participation in {GIS} via mobile applications. {*ISPRS*} *Journal of Photogrammetry and Remote Sensing*, 114:306 – 315, 2016.

[8] Fausto D'Antonio, Paolo Fogliaroni, and Tomi Kauppinen. Vgi edit history reveals data trustworthiness and user reputation. In *17th AGILE International Conference on Geographic Information Science (Short Paper)*, 2014.

[9] Helen Dorn, Tobias Törnros, and Alexander Zipf. Quality Evaluation of VGI Using Authoritative Data - A Comparison with Land Use Data in Southern Germany. *ISPRS International Journal of Geo-Information*, 4(3):1657–1671, 2015.

[10] Michael F. Goodchild and Linna Li. Assuring the quality of volunteered geographic information. *Spatial Statistics*, 1:110 – 120, 2012.

[11] Denis Havlik, Javier Soriano, Carolos Granell, Stuart E. Middleton, Hylke van der Schaaf, Arne Berre, and Jasmin Pielorz. Future internet enablers for VGI applications. In *EnviroInfo 2013*. September 2013.

[12] Roula Karam and Michele Melchiori. A crowdsourcing-based framework for improving geo-spatial open data. In *2013 IEEE International Conference on Systems, Man, and Cybernetics*, pages 468–473. IEEE, 2013.

[13] Carsten Keßler, Johannes Trame, and Tomi Kauppinen. Tracking editing processes in volunteered geographic information: The case of openstreetmap. *Identifying objects, processes and events in spatio-temporally distributed data (IOPE), workshop at conference on spatial information theory*, 12, 2011.

[14] Peter Mooney, Padraig Corcoran, and Blazej Ciepluch. The potential for using volunteered geographic information in pervasive health computing applications. *Journal of Ambient Intelligence and Humanized Computing*, 4(6):731–745, 2013.

[15] Hansi Senaratne, Amin Mobasheri, Ahmed Loai Ali, Cristina Capineri, and Muki Haklay. A review of volunteered geographic information quality assessment methods. *International Journal of Geographical Information Science*, May 2016.

[16] H. Yu, Z. Shen, C. Leung, C. Miao, and V. R. Lesser. A survey of multi-agent trust management systems. *IEEE Access*, 1:35–50, 2013.

[17] Yijiang Zhao, Xiaoguang Zhou, Guangqiang Li, and Hanfa Xing. A Spatio-Temporal VGI Model Considering Trust-Related Information. *ISPRS International Journal of Geo-Information*, 5(2):10, 2016.