Geo-reCAPTCHA: Crowdsourcing Large Amounts of Geographic Information from Earth Observation Data

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Abstract:

The reCAPTCHA concept provides a large amount of valuable information for various applications. First, it provides security, e.g. for a form on a website, by means of a test that only a human could solve. Second, the effort of the user for this test is used to generate additional information, e.g. digitisation of books or identification of house numbers. In this work, we present a concept for adapting the reCAPTCHA idea to create user-generated geographic information from earth observation data, and the requirements during the conception and implementation are depicted in detail. Furthermore, the essential parts of a Geo-reCAPTCHA system are described, and afterwards transferred, to a prototype implementation. An empirical user study is conducted to investigate the Geo-reCAPTCHA approach, assessing time and quality of the resulting geographic information. Our results show that a Geo-reCAPTCHA can be solved by the users of our study on building digitisation in a short amount of time (19.2 s on average) with an overall average accuracy of the digitisations of 82.2%. In conclusion, Geo-reCAPTCHA has the potential to be a reasonable alternative to the typical reCAPTCHA, and to become a new data-rich channel of crowdsourced geographic information.

1. Introduction

Almost every internet user has used it so far - unconsciously providing valuable information for the digitisation of books: a reCAPTCHA (figure 1). The basic idea of a CAPTCHA (von Ahn et al. 2003) is to provide a test that only a human can solve, and that is simultaneously almost unsolvable for a machine. Thus, CAPTCHAs are commonly used to protect login forms from hacking attempts or to prevent users from email spam as a part of contact forms. The most common type of CAPTCHA presents distorted text that has to be identified. However, other CAPTCHA types, e.g. image-based or audio-based, do exist as well.

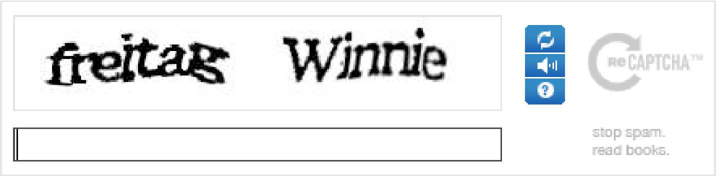


Figure 1. A typical reCAPTCHA presenting two words to be identified by the user. (Google 2014a)

A reCAPTCHA (von Ahn et al. 2008) extends this idea and uses the effort of the user to solve this test for a greater good. It presents two words to the user (figure 1), with one of the two words already known, which serves as a control word to identify an actual human user. The second word is unknown to the reCAPTCHA system itself, meaning that it cannot be automatically recognized with Optical Character Recognition (OCR) software. As the user cannot differentiate between the control word and the unknown word, both words have to be identified. With this crowdsourcing method, thousands of books have been digitised in the past years, with an accuracy of 96.1% over 1 billion responses (von Ahn et al. 2008). Nowadays, reCAPTCHAs are found on 328,117 websites at the time of writing (builtWith 2014).

Geographic information is defined by Goodchild (1997) as the knowledge about where something is located and what is to be found at a given location. This paper presents a novel enhancement of the reCAPTCHA idea, and adapts it to the geographic information domain. We term this system "Geo-reCAPTCHA". Certainly, the system has to fulfil the same requirements as a typical reCAPTCHA, i.e. to provide a test that only humans can solve. Furthermore, Geo-reCAPTCHA is designed to create geographic information from earth observation data for subsequent applications. Such user-generated geographic information (UGGI) is already a crucial part of many recent applications in the field of Geography and Geographic Information Science (GIScience). In addition, several different concepts are ubiquitous in GIScience like Volunteered Geographic Information (VGI), or Citizens as Sensors (Goodchild 2007), describing information captured from people. However, all these terms are united under the generic term UGGI, meaning all information captured directly (e.g. capturing of geometries by users) as well as indirectly (e.g. extracted from location-based social media data; cf. Roick and Heuser 2013). Prominent examples of applications depending on UGGI are OpenStreetMap (OSM) (OpenStreetMap 2014a) or Wikimapia (Wikimapia 2014). Two properties regarding UGGI have to be addressed in this context: i) the users' heterogeneity and ii) the reliability and quality of the information. The users' heterogeneity (i) for OSM is illustrated by Neis and Zipf (2012), showing that only 5% of the users are mapping frequently, whereas 19% are non recurring members. However, frequent users are more trained and are therefore supposed to generate more reliable information. Data errors, and abuse or vandalism, represent the major problems regarding the reliability and quality (ii) of UGGI (Neis et al. 2012). Geo-reCAPTCHA addresses both issues with redundancy of geographic information analogous to the idea of reCAPTCHA.

The main objective of this article is to present a generic conceptual design for a Geo-reCAPTCHA system. Based on this, a Geo-reCAPTCHA infrastructure architecture is proposed, leading to a prototype implementation that allows capturing UGGI. Using this prototype, we conduct a proof-of-concept by means of an empirical user study in which capturing time and quality of the geographic information are investigated.

2. Background and Related Works

This section will provide background information and requirements of CAPTCHA as well as the idea behind reCAPTCHA. Furthermore, the ongoing research regarding UGGI is analysed.

2.1. CAPTCHA and the reCAPTCHA idea

The term CAPTCHA was introduced by von Ahn et al. (2003), and is an acronym for "Completely Automated Public Turing test to tell Computers and Humans Apart". However, CAPTCHA is a special form of a Reverse Turing Test, also known as Human Interactive Proof. It provides a test that can easily be solved by humans, in contrast to machines. CAPTCHAs can be classified based on the medium used for the testing, such as texts, images or audio files. An overview of algorithms and methods for all classes of CAPTCHAs is given by Hidalgo and Alvarez (2011), and more recently by Roshanbin and Miller (2013). The most common CAPTCHA is the text-based CAPTCHA (e.g. "BaffleText" by Chew and Baird 2003). This method presents a text fragment that is modified by distortions and disruptions. Those modifications make an automatic analysis by Optical Character Recognition (OCR) software more difficult. On the other hand, a human user can still read the text and easily pass the test. Another class of CAPTCHAs are the image-based CAPTCHAs. A recent approach is introduced by Kim et al. (2010) using rotated cut-outs of an image. The user has to find the correct orientation of the sub-images by rotating them in order to pass the test.

A rethinking of the CAPTCHA technology is made by von Ahn et al. (2008) by introducing the text-based reCAPTCHA. Instead of using one word for the test, reCAPTCHA presents two words to the user: one unknown word that cannot be identified with OCR software, and a control word for which the answer is known. By typing the control word correctly, the system identifies the user as a human and considers the unknown word as correct as well. Therefore, it is essential that the user cannot differentiate between the control word and the unknown word. The accuracy of the word identification increases depending on the amount of user results for a specific unknown word. The idea of reCAPTCHA is used to digitize words from old printings, for which automatic software has failed. With this approach over 440 million words were correctly deciphered in one year with an accuracy of 96.1% over 1.2 billion responses (von Ahn et al. 2008). However, these numbers are from the year 2008, in which reCAPTCHA was not as well known or commonplace as today. In comparison with 2008, when reCAPTCHA was deployed in ca. 40,000 Web sites (von Ahn et al. 2008), the number of Web sites with reCAPTCHA has risen to 328,117 (builtWith2014) as of the day of writing. Concerning security, the hardest reCAPTCHA has recently been defeated with 99.8% accuracy by Google's own development team using neural networks (Goodfellow et al. 2014). Thus, they concluded that the security of using distorted text for a CAPTCHA test is "significantly diminished".

The geographic or spatial aspect regarding CAPTCHA systems has not played an important role. So far, localized CAPTCHAs are one basic approach. Fiads and Voyiatzis (2013) state that English words or the Latin alphabet are not suitable for a majority of internet users today. As a result, CAPTCHA systems with different languages or alphabets have been presented, like the system introduced by Banday and Shah (2011) for India in the Urdu language, using the IP address to geo-locate the user. Another example for this is the text-based CAPTCHA using Chinese characters proposed by Gustafson and Li (2013). GeoCAPTCHA described by Wei et al. (2012) is an actual image-based CAPTCHA that considers the geographical surrounding. This CAPTCHA scheme uses personalized contents in the form of rotated 3D street-view images. However, no current CAPTCHA approach with a spatial component uses the idea of reCAPTCHA to produce user generated geographic information.

2.2. User-Generated Geographic Information (UGGI)

The well-known OpenStreetMap (OSM) is one of the most popular projects of VGI acquisition and usage. OSM is a free map of the world created by over 1.7 million volunteers interested in mapping (OpenStreetMap 2014b). For many regions of the world, the data density of the map is remarkably high (Raifer 2014), with many different geographic features that can be tagged, like aerial ways, shop types, or tourist destinations (OpenStreetMap 2014c). However, the map is certainly not complete for all parts of the world, and is prone to errors and vandalism (Haklay et al. 2010, Neis et al. 2012). A different idea is pursued by Wikimapia: describe any place on Earth. Therefore, it offers the possibility to add information to a specific location in the form of rectangles or polygons with attached information (in the form of a Wiki). A related approach is adapted by Tomnod (2014), which uses satellite images to solve current problems in specific campaigns, like the mapping of damage caused by the Oklahoma Tornado from 2013 (DigitalGlobe 2014), or finding missing Malaysian Airlines flight 370 (CNN 2014). For each campaign, a small set of tags is available to the user, who can freely navigate through the satellite imagery searching for relevant objects to tag. A similar concept is used by the Geo-Wiki project (Geo-Wiki 2014) to improve global land cover maps. For this purpose, volunteers classify land cover using high resolution imagery in Google Earth through different crowdsourcing campaigns run by the Geo-Wiki team (Fritz et al. 2009, Fritz et al. 2012). However, all those platforms and projects are dependant on volunteers and their commitment and ambition to contribute.

For this reason, Geo-Wiki additionally uses simple user interfaces in the form of a game called Cropland Capture to attract more people (See et al. 2014). Using games as a possibility to generate geographic information has recently become very popular in science and economics (Matyas et al. 2012, Jordan et al 2013), as it makes it easier to attract volunteers. The company

Pallas Ludens (Pallas Ludens 2014), for example, offers the possibility to integrate annotation tasks in games to address millions of gamers.

A comprehensive overview of VGI developments and research is presented by Neis and Zielstra (2014). The reliability and credibility of VGI, with a focus on OSM, is in particular addressed in their work, as this has often been questioned in the past (e.g. Flanagin and Metzger 2008, Comber et al. 2013, Foody et al. 2013). Despite these issues, UGGI is integrated in many different applications. This can be in the form of background data for location-based apps on mobile devices like games (e.g. BucketMan (Google 2014b)), or navigation (e.g. Locus Map Free (Google 2014c)), as well as applications, in the context of Smart Cities and Digital Earth, like CITI-SENSE (CITI-SENSE (2014)) or WeSenseIt (WeSenseIt (2014)). The possibility of generating a large amount of geographic information in a short period of time makes UGGI systems especially relevant and important, particularly for time-critical applications such as disaster response (Middleton et al. 2014), e.g. the rapid mapping activity presented by Reimer et al. (2014) for the crisis in the Philippines following typhoon Haiyan. Over 200 participants mapped valuable information for relief workers in two mapathons. Relevant user-generated information in the form of geolocated photos from the platforms Flickr and Instagram were provided as well.

2.3. Implications for a Geo-reCAPTCHA concept

To the knowledge of the authors there is currently no approach among the geo-related CAPTCHA approaches that extends the reCAPTCHA idea and actually produces geographic information. In fact, only a few approaches take the user’s geographic location into account at all. This gap between the need for complete and updated geographic information and the need for platforms to generate them should be filled with this work. Therefore, a conceptual design for such a UGGI generating system is developed. Based on our review of the aforementioned related works concerning CAPTCHA and reCAPTCHA as well as UGGI, we conclude with the technical requirements listed in table 1, which have to, or should be, addressed during the Geo-reCAPTCHA system design.

Table 1. List of technical requirements that have to, or should be, addressed during the Geo-reCAPTCHA system design.

No.	Technical Requirement
1	HAVE TO tell computers and humans apart (von Ahn et al. 2003)
2	HAVE TO be solvable in an acceptable amount of time (analogous to reCAPTCHA)
3	HAVE TO avoid the user distinguishing between control and unknown data
4	SHOULD use the same type of CAPTCHA for the control and the unknown data
5	SHOULD not exclude certain groups of people (regarding language, age, etc.)
6	SHOULD generate valuable geographic information (regarding reliability, quality, and quantity)

3. Methodology

Based on the technical requirements (table 1), a conceptual design for a UGGI generating system called "Geo-reCAPTCHA" is developed, which adapts the reCAPTCHA idea to the geo-domain. Furthermore, a web-based prototype is implemented, which is then used to conduct an empirical user study.

3.1. Conceptual Design

The main idea of Geo-reCAPTCHA is to use human knowledge to solve the CAPTCHA, and to collect valuable geographic information at the same time. Such geographic information comprises the geometric representation of spatial features (e.g. the floor plan of a house, point location of a tree) and non-geometric, thematic, and semantic information (e.g. type of land use, damage or no-damage). The type of geometry, however, is use case specific and is not relevant for the generic concept.

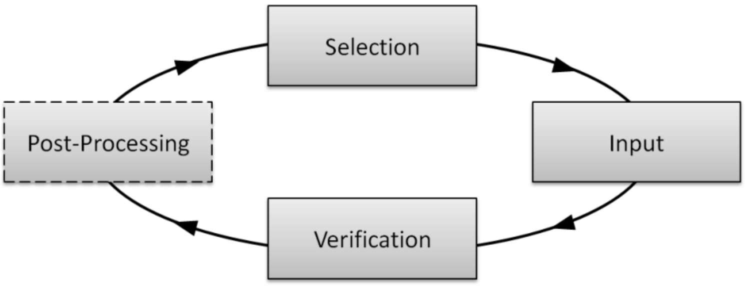


Figure 2. Geo-reCAPTCHA activity diagram consisting of the four main steps.

An overview of the essential steps for a Geo-reCAPTCHA is provided by the basic activity diagram in figure 2. These four generic steps displayed in figure 2 have to be addressed in every implementation of such a system. Subsequently, each step and the corresponding mandatory parameters are presented in detail.

Selection

Each use case requires different basic data for the Geo-reCAPTCHA system (e.g. cadastre data, or remote sensing data for a specific geographic region). In the selection step, the system has to pick parts of the data (e.g. a small subset of the remote sensing data) that is used for the user input in the next step. Therefore, two main preliminary parameters have to be set. First, the known and the unknown data have to be defined. In this case, both parameters describe a data source (or a link to a data source) from which data are gathered or stored. This definition implies the spatial extent for the data capturing which can be different for the known and unknown data. The known data are used as the control data for the CAPTCHA whereas the unknown data are newly captured from the user. After the setting of both essential parameters, the selection step chooses a feature or a geographic extent from the two data sources and delivers the information to a client. In this process, it should be possible to define favoured regions (e.g. a specific city or a disaster region) from which features are selected more often in order to emphasise specific areas. Furthermore, additional information can be used to ensure that certain features are included in the data selection (e.g. compare with OSM data to make sure that a building is visible in an aerial image).

Input

A Geo-reCAPTCHA has to provide an input interface for the user. This interface can differ depending on the type of geographic information being captured. This information can be geometric (e.g. point, line, polygon, or point cloud) as well as non-geometric (e.g. context, topology, semantics). In the geometric case, the geometry class has to be defined. The classes can be derived from the Open Geospatial Consortium (OGC) simple feature specification (OGC 2011). Although *Geometry* class is capable of being integrated in the concept, it is recommended that the class *GeometryCollection* be excluded to keep the system simple for the user. This means that only one feature at a time should be captured from the user. Thus, the system has a higher chance of achieving the technical requirement to be solvable in an acceptable amount of time (table 1).

In the non-geometric case, it has to be defined whether i) a collection of given values is presented to the user or ii) the user can type free text. In the first case, the expected user input is known (e.g. taken from existing feature attributes of projects like OSM or GeoWiki) and thus the interpretational efforts during the postprocessing are much less complex. The possibility to type free text in the second case has pros and cons. On the one hand, the results might be much more accurate due to the freedom of the user input and the fact that the user is not limited to pre-defined options. On the other hand, it may require significantly more effort to interpret the user input since the actual meaning has to be extracted and analyzed. Furthermore, the interpretation of free text (automatic, semi-automatic, or manual) may result in a misinterpretation of the information.

Afterwards, corresponding capturing tools have to be provided for the user input. For this purpose, it is important that the user cannot distinguish between the input for the control data and for the unknown data, as defined in the technical requirements (table 1). If this was not the case, the user could simply enter the control data to pass the CAPTCHA, but the unknown data would not be reliable. This is also the reason why one cannot simply mix up different types of CAPTCHA (according to the technical requirements) in a reCAPTCHA system (e.g. text-based CAPTCHA and a map input for unknown data) as the user is expected to avoid the input of the unknown data to save time.

Verification

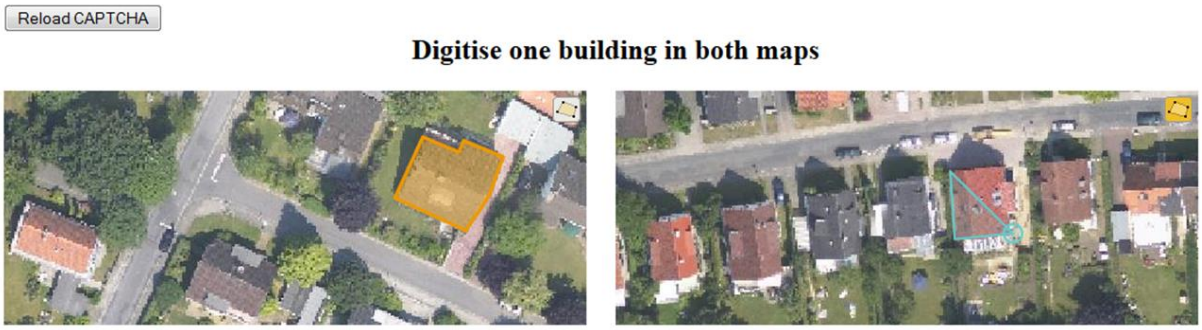
The most important part of the system is the actual verification of whether the CAPTCHA is passed or not, i.e. whether the input was made by a human user or a machine. The verification has to be adapted to the type of information captured from the user, and has to compare the captured information with the control data. This testing is completely use case specific and can vary in its complexity. For example, it can be a rather complex comparison of two geometries (e.g. a floor plan of a house) to determine equality, or a simple word check between the input of the user and a pre-defined set of correct values.

Postprocessing

During the postprocessing step the verified information of the user is analysed or combined with other data to generate an additional value or to solve a specific problem (for example, deriving one building outline out of all user digitisations for one object). This step should be an integral part of a Geo-reCAPTCHA. Analogous to the verification step, the postprocessing is use case specific as well. It can vary from simply storing every user input (e.g. for visualisation purposes), to complex heuristics and analysis (e.g. comparing digitised building geometries with building data derived from remote sensing imagery for change detection approaches). Furthermore, additional external data sources can be included in the postprocessing step (e.g. land cover classifications from remote sensing data).

3.2. Prototype Implementation

The four essential steps from the conceptual design are transferred into a Web infrastructure design. As a proof-of-concept, a Geo-reCAPTCHA prototype is implemented in which the user has to digitise the boundary of buildings from airborne imagery as illustrated in figure 3. A generic overview of the infrastructure design for this prototype is illustrated in figure 4. The essential parts are subsequently described in detail.



Digitise one building in both maps

Figure 3. Prototype implementation of a Geo-reCAPTCHA client. Two map representations offer the possibility to digitise building boundaries in the form of polygons. The digitisation in the left map is already completed (yellow polygon) whereas the digitisation in the right map is currently in progress (blue sketch).

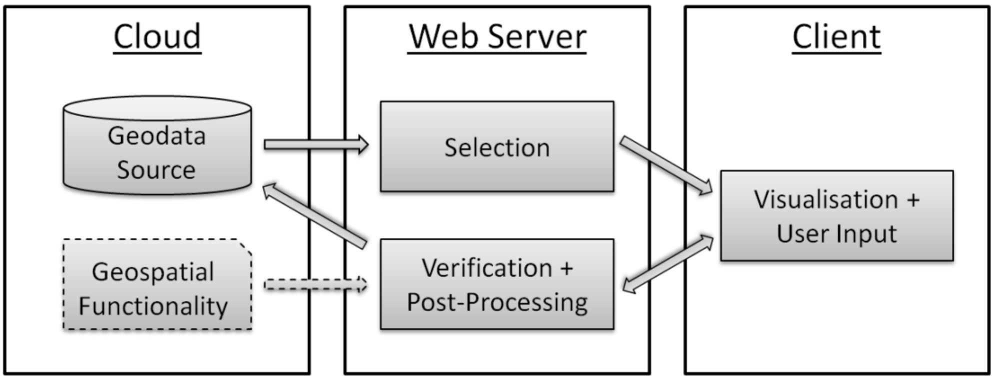


Figure 4. Infrastructure design for a web-based Geo-reCAPTCHA prototype consisting of a cloud component, a web server, and a client.

Web Server

The web server builds the centrepiece of the infrastructure design by managing all incoming requests of the client, building the bridge to the geodata sources and holding the logic of the

Geo-reCAPTCHA system in the form of selection, verification, and postprocessing functionality. The initial point is the selection step in which the essential parameters "type", "unknown data" and "control data" have to be defined.

The information type defines whether the user has to digitise geometries or has to capture non-geometric information. The prototype implemented in this work will capture geometric information in the form of polygons. According to the information type, the control data and the unknown data have to be defined, e.g. by defining a region and a base layer from which the data are extracted. The selection process can now randomly fetch data from the given data sources or with emphasis on one or more defined favoured regions within the data. For our prototype, aerial images are provided by an OGC Web Map Service (WMS) for both control and unknown data.

The second part of the web server consists of the verification and the postprocessing steps as outlined in the generic concept. The verification process is called by the client after the user inputs data. As it is defined in the conceptual design, it has to be decided whether the user input matches the control data or not. The presented Geo-reCAPTCHA prototype verifies the input using a simple algorithm that builds a buffer around the boundary of the control geometry and checks whether the boundary of the polygon digitised by the user lies completely within this buffer area.

If the user input for the control data is evaluated as correct, a message will be sent to the client to confirm the (successful) passing of the CAPTCHA. Simultaneously, the input of the unknown data is considered to be correct as well and can therefore be integrated into the postprocessing procedure. The prototype currently has no automatic postprocessing implemented as the interpretation is done manually in the course of the empirical user study.

Client

The client is the interface for the user with which input can be captured and transferred to the web server. In the prototype, the client is a typical website displayed within a standard browser. The website requests the relevant data for the Geo-reCAPTCHA from the web server and visualises it for the user in two map representations (figure 3). One map shows the selected data of the unknown data whereas the other map shows the control data. If a specific feature is pre-selected for capturing, it has to be marked somehow in the map to make sure that it can be correctly identified by the user. However, it has to be assured that the user cannot identify the map representation that displays the control data (technical requirements in table 1).

Each of the two map representations has to provide a digitisation tool (as implemented in the prototype in figure 3) with which the user can capture the selected geometry type (e.g. a polygon or a linestring). The tool has to follow certain specifications: First, only the geometry type defined for the CAPTCHA is allowed in the digitisation process. Switching between geometry types is not recommended. After the user finishes the digitisation of the first geometry, the tool has to be disabled so that no further geometry can be captured from the user. No edit or delete functionality is provided to keep the system as simple as possible. However, the user can reload the map representation to receive new data from the server, and restart the digitisation. For a non-geometric Geo-reCAPTCHA, additional input tools are needed like a selection box with pre-defined labels or a text field for free user input.

After both inputs of the user, the client automatically submits the result to the web server. Subsequently, the web server returns the result of the verification process. If the test is passed, the user can proceed. If the test is failed, the website will reload the test and request new data from the server.

Cloud

The cloud in this case describes any place, server, service, or resource in general, from the Web. This also includes local geodatabases as well as geospatial functions from a programming library installed on the Geo-reCAPTCHA web server itself. The cloud component of the infrastructure design specifies these resources to geodata sources and the optional geospatial functionality.

3.3. Empirical User Study

An empirical user study has been conducted to investigate how long our CAPTCHA approach within the Geo-reCAPTCHA prototype takes to be solved, and to derive the accuracy of the derived UGGI. In general, everyone aware of the user study was able to participate. However, specific advertisement was made among students and staff members of the Institute of Geoinformatics and Remote Sensing in Osnabrueck (Germany) and the Institute of Geography in Heidelberg (Germany). Additionally, many participants are geography students consulted during a basic geography lecture at the University of Vienna (Austria). Thus, the following user groups are assumed to participate: Student of natural science, student of non-natural science, student of geography, student of geoinformatics or similar, geoinformatics expert, none of the listed groups.

In the experimental setup, the user is challenged to digitise the outlines of 15 consecutive arbitrary buildings from the map representation in a fast but convenient way. Our study area contains simple building footprint shapes (e.g. rectangular) and also difficult cases where the building is composed of several parts (e.g. attached garage) and also cases where trees are adjacent to the building. This selection of different building situations will allow us identifying the limitations of building digitization in Geo-reCAPTCHA, such as best and worst-case buildings. Each digitisation is recorded with a randomly generated user identifier to estimate the overall number of participants as it is not allowed to simply store the users' IP address. This identifier changes when the same user opens the site again which is why users are able to redo the study. Due to this fact, we cannot provide an exact number of participants but a number of digitisation rounds with the same user identifier.

Table 2. List of data that are gathered in the empirical user study.

Name	**Description**
GEOMETRY	The geometry of the digitised building outline
TIME	The time for finishing the digitisation (in s)
USER GROUP	The user group in the categories as mentioned above
AGE	The user’s age in the categories: 18 – 24, 25 – 34, 35 – 44, 45 – 60, > 60, no age selected
TIMESTAMP	The timestamp of the digitisation (date and time)
POINTID	The identification number of the different centres of the map view

USERID	The identification number which is created randomly for each user to identify digitisations from the same user
COUNTER	The counter that represents the number of digitisations done by the user

The description of the test for the user was generically formulated to avoid influencing the user's behaviour during digitisation. It was not mentioned in the task description that the user should be as fast or as accurate as possible. Before starting with the actual digitisation, the user is requested to give basic information about age and user group (or rather experience level). Afterwards, a reduced version of the prototype with only one map representation is presented to the user. In this case, 25 pre-defined centre points for the map view are available to make sure that a building is visible for each digitisation run. This leads to an extensive overlap of the UGGI and allows for substantial statistical analysis of the accuracy of the captured geometries. The time from the first click in the map to the moment when the user finishes the digitisation with a double-click is recorded and stored. The prototype implementation of the experiment does not permit editing or deleting of digitised features. However, the user has the option to withdraw the capture by reloading the map representation with new data and thus a new test. This function should be used if the user is not able to identify a building within the dataset. Each reloading process is recorded and stored in the database in order to investigate the reasons for reloading and withdrawing tests. The empirical experiment is finished for the users as soon as 15 buildings have been digitised. The structure of the gathered dataset is described in table 2.

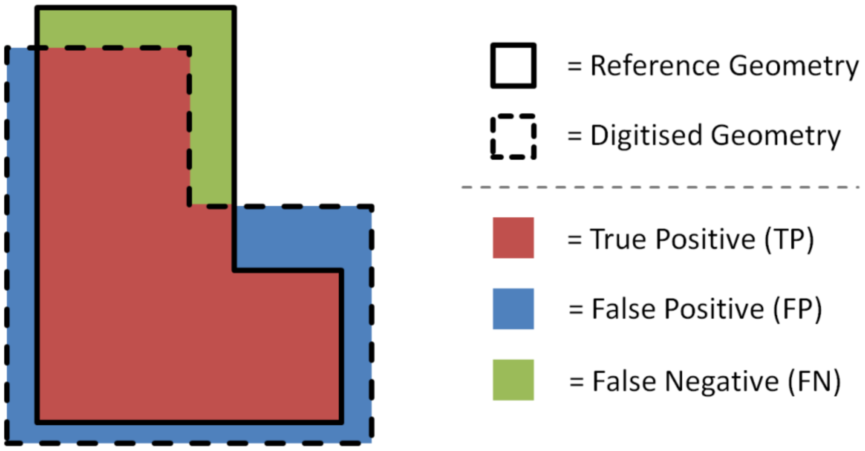


Figure 5. Three initial quality measures based on the overlapping and non-overlapping areas between the reference (solid polygon) and digitised (dashed polygon) geometries.

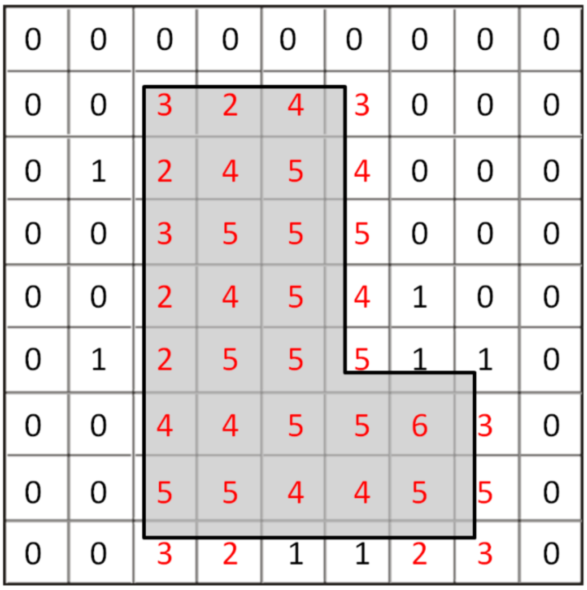
Furthermore, standard quality measures for building extraction are derived for each building (cf. Rutzinger et al. 2009; Heipke et al. 1997). Each digitised geometry is compared to a reference with which the digitised geometry shares the most overlapping area. In a first step, three measures are derived based on the overlapping and non-overlapping areas between the reference (solid polygon) and the digitised (dashed polygon) geometries (figure 5). The true positive (TP) area is the one that exists in both polygons (consensus), i.e. intersection area in GIS terminology. In contrast, the area that appears only in the digitised geometry is classified as false positive (FP). The area that is not digitised by the user but is actually part of the reference geometry is the false negative (FN) area. Consequently, the TP-rate (completeness), the precision (correctness), and the overall quality of the digitised geometry can be calculated with the following equations (cf. Rutzinger et al. 2009):

$$TP\text{-}rate\ (completeness) = \frac{TP}{TP+FN} \tag{1}$$

$$precision\ (correctness) = \frac{TP}{TP+FP} \tag{2}$$

$$quality = \frac{TP}{TP+FP+FN} \tag{3}$$

Furthermore, it is analysed how many digitised geometries are needed to receive appropriate results that almost match the corresponding reference geometry. For this purpose, the idea of a raster-based quantitative analysis by Klonner et al. (2014) is adapted. The idea is to build a raster with a specific cell size and sum up the number of polygons within each cell. An estimation for an appropriate number of digitised geometries can be derived by comparing the boundary of the reference geometry with the raster grid (figure 6). Thus, for a Geo-reCAPTCHA implementation a threshold for the transition from unknown to known data has to be set.



0	0	0	0	0	0	0	0	0
0	0	3	2	4	3	0	0	0
0	1	2	4	5	4	0	0	0
0	0	3	5	5	5	0	0	0
0	0	2	4	5	4	1	0	0
0	1	2	5	5	5	1	1	0
0	0	4	4	5	5	6	3	0
0	0	5	5	4	4	5	5	0
0	0	3	2	1	1	2	3	0

Figure 6. Reference polygon (grey) with overlaying raster grid. The raster is filled with the respective number of digitised polygons for each raster cell. Values above 1 are coloured red and are used for estimating the reference geometry.

4. Results

The conceptual design was implemented in a prototype, which was used for a proof-of-concept in the form of an empirical user study. Within the two weeks of the empirical user study, 2260 geometries were digitised in 189 total digitisation rounds. As users could also digitize multiple times, the number of unique users might be lower than the number of digitisations. The distribution of the digitisations among user groups and age groups of the users is presented in table 3. According to the user selection, most geometries are digitised by students of geography with 950 (42.0%) followed by geoinformatics experts (531 geometries (23.5%)) and students of geoinformatics or similar (428 geometries (18.9%)). As the study was promoted in a basic lecture in geography, it can be assumed that most of the students of geography do not have much expertise regarding geoinformatics. Furthermore, most geometries are digitised from users with an age from 25 to 34 years with 1285 geometries (56.9%) as well as 18 to 24 years with 700 geometries (31.0%). People with an age of 45 and above are not well represented in this user study (60 geometries, 2.6%). The options "None of the listed groups" for the user group and "No age selected" for the age were the default values for the selection boxes in the user study.

Table 3. Distribution of digitisations among the categories user group and age of the participants of the empirical user study.

Age User group	18 -24	25 - 34	35 - 44	> 45	No age selected	Total
Student of natural science	1	90	0	0	0	**91 (4.03%)**
Student of non-natural science	30	30	0	0	0	**60 (2.65%)**
Student of geography	499	451	0	0	0	**950 (42.03%)**
Student of geoinformatics or similar	142	259	27	0	0	**428 (18.94%)**
Geoinformatics expert	13	363	125	30	0	**531 (23.49%)**
None of the listed groups	15	92	15	30	48	**200 (8.85%)**
Total	**700 (30.97%)**	**1285 (56.86%)**	**167 (7.39%)**	**60 (2.65%)**	**48 (2.12%)**	**2260 (100.00%)**

4.1. Digitisation Process

In a first step, the time for digitising an arbitrary building in comparison with the derived quality is analysed. The recorded time is almost normally distributed with an average of 11.3 s and a standard deviation of 74.5 s over all 2260 digitised geometries for 68 different building objects. The high standard deviation is caused by three very long digitisation times (way above 60 s) with a maximum of 3527 s (almost 59 min). Removing those three datasets, the average digitisation time changes to 9.6 s with a standard deviation of 6.9 s. The following analysis will be based on the cleaned datasets.

Table 4. Descriptive statistics of all digitisations regarding the digitisation time (in s) and quality (in %) of one building divided by user groups.

		Digitisation time for one building [s]				**Quality of one building [%]**			
User group	**N**	**Min**	**Max**	**Mean**	**Std. dev.**	**Min**	**Max**	**Mean**	**Std. dev.**
Student of natural science	91	2.8	39.0	11.4	6.7	0	97.0	79.6	24.2
Student of non-natural science	60	3.2	49.4	12.1	9.6	0	95.5	79.5	22.4
Student of geography	949	2.1	44.2	8.6	5.8	0	97.6	82.4	20.5
Student of geoinformatics or similar	426	2.2	57.0	10.4	8.0	0	98.3	83.3	18.3
Geoinformatics expert	531	2.3	59.9	9.5	6.9	0	97.9	83.9	18.2
None of the listed groups	200	1.4	56.1	11.5	7.4	0	96.9	76.8	28.1

Table 5. Descriptive statistics of all digitisations regarding the digitisation time (in s) and quality (in %) of one building divided by age groups.

		Digitisation time for one building [s]				**Quality of one building [%]**			
Age group	**N**	**Min**	**Max**	**Mean**	**Std. dev.**	**Min**	**Max**	**Mean**	**Std. dev.**
No age selected	48	1.4	35.5	11.3	7.3	0	94.1	59.9	33.5
18 - 24	699	2.3	56.1	9.6	6.6	0	97.7	83.5	19.1
25 - 34	1283	2.1	57.0	9.2	6.9	0	98.3	82.6	20.2
35 - 44	167	3.8	59.9	11.1	7.6	0	97.2	81.5	20.2
> 45	60	5.1	32.7	12.7	6.9	0	97.2	78.9	27.6

Furthermore, time and quality are analysed in detail to determine differences between user groups and groups of age. Table 4 shows the results for the corresponding user groups. Students of geography are digitising one second faster in the mean (8.6 s) than the geoinformatics experts (9.5 s), which are the second fastest group. The quality of the experts, however, is slightly higher in the mean (83.9% compared to 82.4%) with a lower standard deviation (18.2% to 20.5%). It can be seen that the groups with geography or geoinformatics background (students of geography, students of geoinformatics or similar and geoinformatics experts) do record the lowest values regarding digitisation time and the highest average qualities of building polygons.

The results for the different age groups can be seen in table 5. Participants with an age between 18 and 34 are generally slightly faster (9.2 s to 9.6 s in the mean) than older participants (10.2 s to 13.5 s in the mean). Regarding the quality of the digitisation, the differences are much smaller between these age groups. The highest quality is recorded for the 18-year to 24-year old users with 83.5%. The 35-year to 44-year old users, however, record only a slightly lower quality of 81.5%. Overall, performing an analysis of variance (ANOVA) and a t-test, the user and age groups do show significant differences regarding digitisation time and quality.

The presented results provide insights into the fulfilling of the two main Geo-reCAPTCHA requirements (table 1). First, it is shown that a map-based CAPTCHA can be solved in an overall mean of 9.6 s. Thus, a total time for a Geo-reCAPTCHA of 19.2 s can be expected as the Geo-reCAPTCHA approach requires two digitisations (for the control and the unknown data). Von Ahn et al. (2008) proved that, on average, the time required to solve a conventional CAPTCHA is 13.51 s and 13.06 s for a reCAPTCHA. Therefore, a Geo-reCAPTCHA does need more time to be solved than a reCAPTCHA. Nevertheless, regarding the effort of other CAPTCHAs like image-based CAPTCHAs, the expected time can be considered acceptable from our point of view as it is less than 50% slower than traditional reCAPTCHA. Furthermore, the results of this user study show that Geo-reCAPTCHA can be solved successfully by any of our user groups.

Moreover, the main Geo-reCAPTCHA requirements ask for the creation of reusable information. An overall quality for a single building of 82.2% on average suggests that this requirement is fulfilled in the specific use case of building digitisation. However, a detailed analysis of the digitisation quality is needed. Additionally, quantitative statements regarding the amount of digitisations that are required for a successful derivation of a valid geometry from Geo-reCAPTCHA have to be determined.

4.2. Quality and redundancy of multiple object digitisations

Using the calculated accuracy parameters, the building objects can be described based on a single user digitisation and also the full track of all digitisations available for each object.

Table 6. Descriptive statistics of the three accuracy parameters TP-rate, precision, and quality (equations 1-3) for all digitised geometries (all values in %).

Accuracy parameter	**Min**	**Max**	**Mean**	**Median**	**Std. dev.**
TP-rate (completeness)	20.4	100.0	88.8	95.06	8.7
Precision (correctness)	22.1	100.0	88.1	95.10	9.2
Quality	20.4	98.3	82.2	88.84	10.7

The three accuracy parameters (equations 1-3) are calculated for each single building digitisation individually. The accuracy statistics of all building digitisations is summarised in table 6. Overall, an average quality of 82.2% with a standard deviation of 10.7% is measured. The mean values for the completeness and the correctness are quite similar with 88.8% and 88.1%, respectively. The maximum values of those two parameters are recorded with 100%. However, this is not surprising as digitisations that are fitting the building footprint or are larger will result in a completeness of 100%, whereas digitisations that are completely inside of the reference geometry (and thus smaller) will deliver a correctness of 100% and completeness values lower than 100%. The mean quality of digitisations is 88.1% for all digitisations with completeness above the median value (95.06%). This indicates that those buildings are digitised very well but presumably slightly larger than the actual building footprint. Likewise, the mean quality of digitisations reaches 89.9% for all digitisations with correctness above the median value (95.10%). Thus, the majority of buildings was captured very well. Here, the quality value of 89.9% indicates that those buildings were digitized slightly smaller than the reference building footprint.

Figure 7 shows the distribution of reloads according to the respective centre points of the map view. It can be seen that some map views (i.e. centred on a certain building) are skipped more often than others. One of the lowest mean qualities for a building (53.6%) is found in the map view with the PointID 12 (figure 8). The structure of the main building is basically rectangular and thus not complex at all. However, it is not obvious which part of the image actually is part of the building or belongs to another object like a garage. Most digitisations in this case are focused on the main building, which results in a poor digitisation quality. The building object with one of the highest average qualities (92.7%) is shown in figure 8. The building has a simple structure that can easily be distinguished from its surroundings.

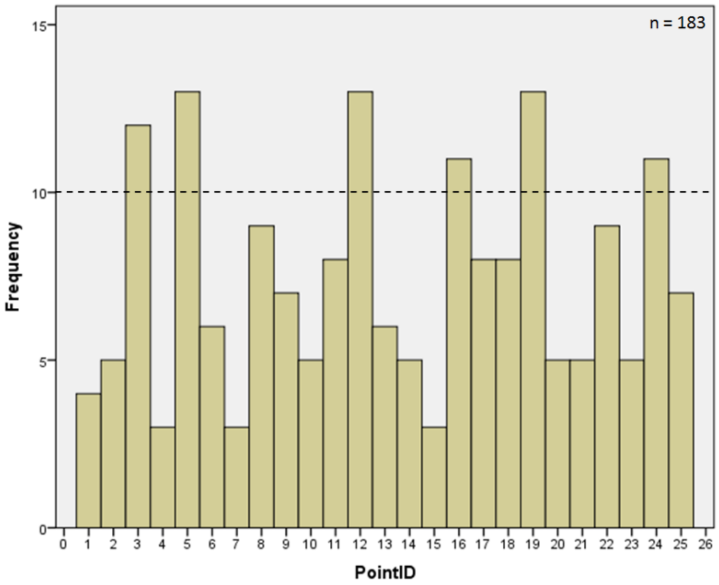


Figure 7. Distribution of reload frequencies for each map centre point.

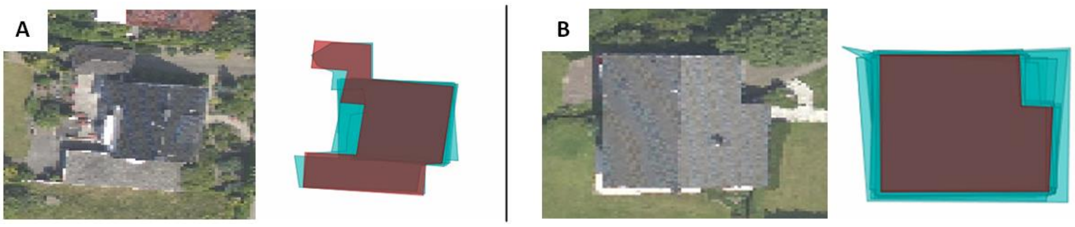


Figure 8. Aerial images and corresponding geometries (reference: red / digitisations: blue) of the building with the lowest overall average quality (53.56%) within the map view of PointID 12 (A) and the building with the highest overall average quality (92.73%) within the map view of PointID 6 (B).

The raster-based analysis of the cumulated geometries (Figure 9 and 10) supports these observations. Both images are classified according to the number of polygons within each raster cell. It is shown that even a low number of digitised geometries deliver an appropriate estimation for the actual building. Figure 9 emphasizes the problem of neighbouring buildings that can or cannot be recognized as a part of the main building by the user. However, the main building itself can be derived from the digitised geometries despite the low overall quality (compared to the reference geometry) of the digitisations for this building. Thus, it can be stated that if all digitisations are combined in to one geometry, the quality of this geometry will be better than the single polygons individually. However, at a certain point, the gain of quality is not significant as the overall quality is already high. Therefore, a threshold for the number of digitised geometries for one building can be defined, at which point the building is approximated accurately. This threshold has to be adapted depending on i) the geometries that are captured from the Geo-reCAPTCHA (e.g. point or polygon) and ii) the method that is used to combine the geometries (e.g. centre point of a point collection, intersection of a polygon collection).

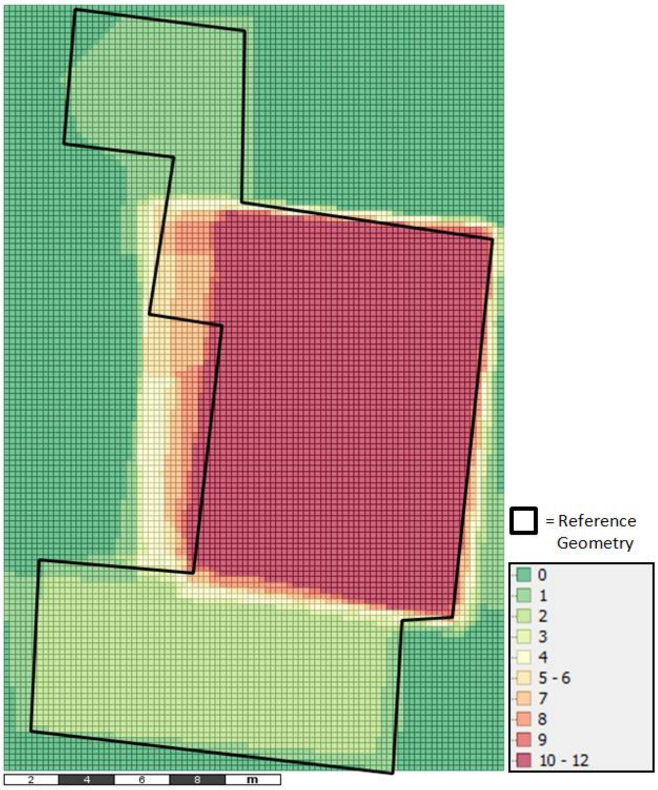


Figure 9. Number of overlapping geometries on an 18.0 m x 27.6 m raster with a cell size of 0.2 m for the building with the lowest overall quality (53.56%).

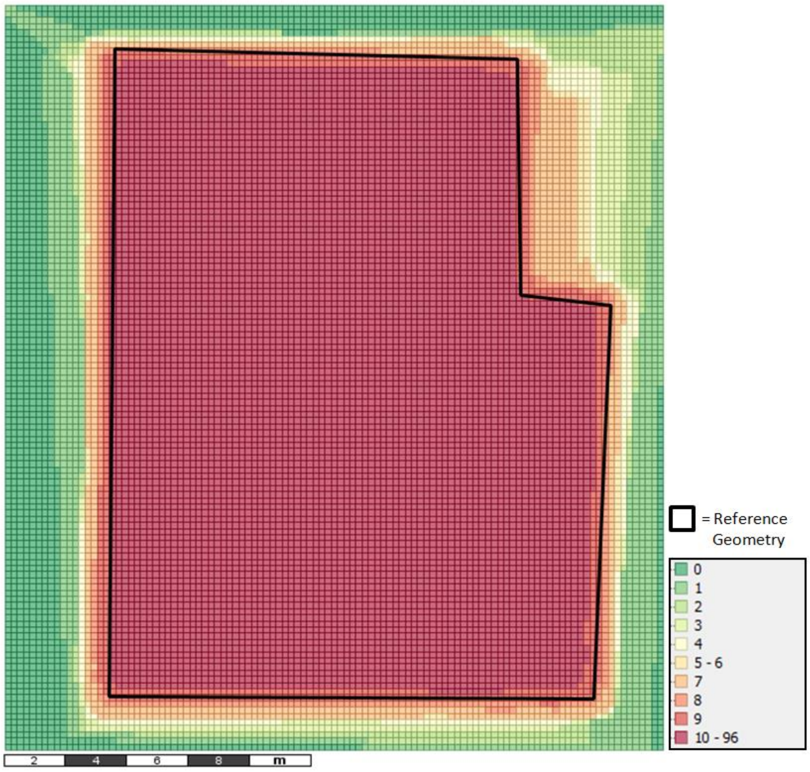


Figure 10. Number of overlapping geometries on a 21.4 m x 24.2 m raster with a cell size of 0.2 m for the building with the highest overall quality (92.73%).

5. Conclusions

In this work, a concept for adapting the reCAPTCHA idea to gather user-generated geographic information from earth observation data is presented. Therefore, the reCAPTCHA concept was extended to provide geographic information instead of text to the user. Digitisation tools allow for capturing new geometries or semantic information about a geographical feature.

The performed Geo-reCAPTCHA user study on building geometry mapping revealed a digitisation time per building object of 9.6 s (average over 2257 geometries) which results in an average total solving time for a Geo-reCAPTCHA of 19.2 s. Furthermore, an average quality of single digitised building polygons of 82.2% was achieved. A detailed analysis shows that the differentiation between the main building and additional buildings is one of the main reasons for poor digitisations. However, the combination of all the single building digitisations allows for an appropriate estimation of the actual building despite the poor quality of some digitisations.

The results of the empirical user study show that a Geo-reCAPTCHA is capable of producing geographic data with high accuracy in a small amount of time for the digitisation of one building. Above that, there are further geographic applications and potential use cases in which data from Geo-reCAPTCHA could be integrated. One use case could be to contribute to the digitisation of base maps in crisis-prone parts of the worlds where maps are missing (MSF UK 2014). Moreover, Geo-reCAPTCHA could be used to classify remote sensing data. For example, Geo-Wiki could utilize Geo-reCAPTCHA to update the global land cover classification by presenting random parts of satellite images in which the predominant land cover class (e.g. forests, agricultural, or urban areas) should be digitised. Beyond that, even 3D earth observation data in the form of laser scanning point cloud data can be classified by identifying objects within the point cloud (e.g. a house or a tree) using Geo-reCAPTCHA. These LiDAR datasets are particularly relevant for establishing reference object libraries, such as for vegetation objects (Koenig et al. 2013) where the large amount of reference object features improves automatic 3D tree characterization.

In conclusion, all technical requirements, which are extracted from our review of the related works (table 1), are addressed in the Geo-reCAPTCHA system design. Thus, Geo-reCAPTCHA offers an appropriate alternative to reCAPTCHA regarding CAPTCHA security as well as the resulting data quality.

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