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Department of Civil and Transport Engineering
TBA4925 - Master Thesis

Optimizing the micro-tasking workflow and exploring it's usage potential within geospatial data

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Trondheim, June 2017

DAIM page

Background

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Task Description

The micro-tasking method is becoming more and more popular. Companies like Amazon develop micro-tasking web applications where people can earn money by doing micro-tasks for others. The method is used for tasks that involve both use of technology and a large number of people. By using the micro-tasking methodology, this thesis aims to study how people solves micro-tasks within geospatial data imports, which is a very complex and large process.

This study will have an emphasis on the data validation and conflict handling part of the import. These parts are complicated to do fully automatic through scripts. By varying the number of objects to solve at a time, adding rewards on some tasks, among other factors, the study will hopefully find a significant approach to prefer when using the micro-tasking method within geospatial data. What are the number of objects optimal within a task to get it completed as quickly as possible? Does the quality of the work vary between the different tasks given? Do amateurs manage to do the tasks? Do rewards have an impact on how the tasks are solved?

This thesis will also explore the micro-tasking methods usage potential within geospatial data. Can other organizations doing a process that needs humans to interfere take advantage of this method? An example is OpenStreetMap, who has taken good advantage of the method both in mapping and import projects.

Specific tasks:

- Study related literature
- Do a micro-tasking survey
- Examine how many elements are optimal when creating geospatial micro-tasks

Abstract

This paper propose a method for extracting buildings in satellite photos. The proposed network makes use of a digital surface model and multispectral satellite data. It

Sammendrag

Sammendrag på norsk

Preface

This paper is a master thesis written for the Department of Civil and Transport Engineering at the Norwegian University of Science and Technology (NTNU) in Trondheim, Norway. It is a part of the study program Engineering and ICT - Geomatics, and was written in the spring of 2017.

I would like to thank my supervisor Terje Midtbø for his help and feedback, and also Atle Frenvik Sveen for his support and help every time I needed it.

Trondhiem, 2017-06-16?
Anne Sofie Strand Erichsen

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1 | Introduction

A task can traditionally be divided by time, place, person, object, and skill [(Meier, 2013b), p. 13]. A task can be created by identifying the time it will require, the place where it must be done, the people who need to do the task, the object on which the work is done and finally, the skill needed for the task. Today we have technology that can create and move tasks around based on the four first categories. Technology can allocate tasks based on the deadline and time the task requires. It can also establish communication between any team of people dependent on which people the task requires. One thing that technology can't do is change the skill of individual workers, though it can only connect people with different skills to work on the same tasks [(Meier, 2013b), p. 14]. Crowdsourcing moves beyond this and looks at the skills of individual workers, the problem that needs to be solved and combines the best skills of workers to solve the problem. The division of labor by skill has more economic impact than the other four categories [(Meier, 2013b), p. 15]. Crowdsourcing is a way of refactoring work in a way that exploits the worker's flexibility and gets the right skills to the right part of the problem. To get the right skills to the right part of the problem it needs to be partitioned into smaller parts. Having smaller parts will make it easier to distribute the problem. The distribution can be done through micro-tasking, also called "smart crowdsourcing" by Patrick Meier (Meier, 2013a).

This thesis aim is to study if micro-tasking can successfully be expanded to involving maps and geospatial data. The OpenStreetMap community has used the method some time, and the usage so far can be evaluated as successful. This thesis also aims to find out if inexperienced individuals also manage to solve tasks on maps that involves geospatial data. The study also aims to determine if the number of elements in each micro-task has an impact on how well individuals solve the micro-tasks. The quality of the work, the number of correctly solved tasks and time, is measured. The thesis uses a survey hosted through a web-application to gather participant data. The data is then used to answer this thesis hypothesizes. The next chapter will give a thorough introduction to micro-tasking and hopefully make it clearer what this thesis aim is. Chapter 3 will explain the survey and chapter 4 will contain the statistics, both hypothesis, theory, and results.

2 | Background

Creating and maintaining real-world knowledge bases in a classical work environment demands a high cost, and is a cost that is often unnecessary [(Meier, 2013b), p. 134]. Alternative approaches are to rely on the knowledge of open crowds, volunteer contributions, or services like micro-tasking platforms where there are people ready to work on the tasks given to them.

Today, geospatial data is more available than ever. Governments are releasing more and more data and the OpenStreetMap database is still growing. While general data availability is increasing, the quality of the data is not necessarily perfect and manual pre-processing is often necessary before using it (Difallah et al., 2015). Pre-processing of the data can require much time and high costs. By exploiting both machines and people through the appropriate platform, the cost can decrease and the quality increase. As you will read in this chapter, combining machines and people is often a better and faster solution than a fully-automatic or fully-manual approach and implementing such an approach into a micro-tasking platform can be a good solution.

2.1 Human computation

Human computing is, at its most general level, computation performed by humans. It is tasks that computers cannot yet perform. Utilizing the human processing power is still important. Humans are necessary even though our computers are becoming more and more complex. Traditional approaches to solving problems are to focus on improving the software, but often a solution that uses humans cleverly by exploiting the human brain's cognitive abilities can sometimes create much faster and better results than a software. One of the pioneers of crowdsourcing, Luis von Ahn, created a game called "The ESP game". HVA ER GAMIFICATION It solves the problem of labeling images with words. Most images don't have a proper caption associated with them and this makes it difficult to create search engines for images for instance. A fast and cheap method of labeling images is by using humans cleverly, humans can very easily see if the image contains a dog or cat for instance. Through "The ESP game" humans where labeling images without even knowing it, they only played a fun game. Within a few months, the game collected more than 40 million image labels (von Ahn, 2008), and they didn't even have to pay them doing it. Another game that was created by Luis Von Ahn is called "Peekaboom". Here the players would locate objects in images. Such information is very useful in computer vision research for instance (von Ahn, 2008). Both games exploited humans abilities in a very clever way, our vision is still better than computers abilities to recognize items in images.

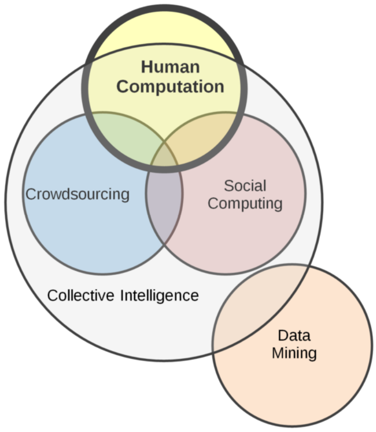


Figure 2.1: Collective intelligence (Quinn and Bederson, 2011)

Human computation, a term introduced by Luis von Ahn, refers to according to Quinn and Bederson (2011) a distributed system that combine the strengths of humans and computers to accomplish tasks that neither can do alone. To make human-computation in crowdsourcing effective one need to know how the results can be optimally acquired from humans and how the results can be integrated into productive environments without having to change established workflows and practices [(Meier, 2013b), p. 134].

2.2 Crowdsourcing

The first time the term "crowdsourcing" appeared was in Wires magazine article by Jeff Howe (Howe, 2006). Whereas human computing (section 2.1) replaces computers with humans, crowdsourcing replaces traditional human workers with members of the public (Quinn and Bederson, 2011). EYeka (2015) state that 85 % of the top global brands use crowdsourcing for various purposes. Crowdsourcing has become a widespread approach to dealing with machine-based computations where we leverage the human intelligence (Gadiraju et al., 2015). Crowdsourcing is an increasingly important concept, where the concept is the completion of large projects by combining small distributed contributions from the public (Salk et al., 2016).

When the scope of a crowdsourced project is explicitly geographical, it is often called *volunteered geographical information* (VGI). According to Salk et al. (2016), the best known VGI project is OpenStreetMap (OSM). OSM is an open-source mapping project, where volunteers contribute with their local knowledge and mapping abilities.

2.3 Micro-tasking

The simplest type of tasks are called micro-tasks and is illustrated in figure 2.2. Micro-tasks should not require any special training and a task should be completed within a couple of minutes (Ipeirotis and G., 2010). Problems that are suitable for solving through micro-tasking are those that are easy to distribute into a number of simple tasks, that can be completed in parallel in a relatively short period of time (from seconds to minutes), without requiring specific skills (Sarasua et al., 2012). Research has also demonstrated that micro-tasking is effective for far more complex problems when using sophisticated workflow management techniques. Micro-tasking can then be applied to a broader range of problems like: (1) completing surveys, (2) translating text between two languages, (3) matching pictures of people, (4) summarizing text (Bernstein et al., 2015), etc.

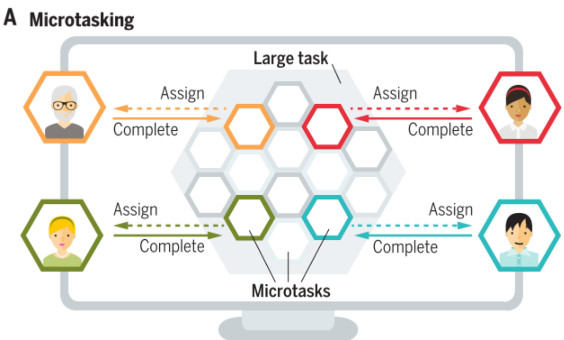


Figure 2.2: Micro-tasking (Michelucci and Dickinson, 2016)

Micro-tasking and human computation are closely related. In the "Handbook of Human Computation", micro-tasking is present in the *Human Computation for Disaster Response* chapter [(Meier, 2013b), p. 95-105], as well as in several other chapters. In the *Human Computation for Disaster Response* chapter they give an overview of how human computation methods, such as paid micro-tasks, could be used to help in major disasters. In 2012, Philippines was struck by a typhoon called Ruby, devastating large regions. With the help of CrowdFlower micro-tasking platform, the workers collected over 20 000 tweets related to the typhoon and identified the tweets containing links to either photos or video footage from the damaged areas. The relevant tweets were uploaded to the CrowdCrafting micro-tasking platform were volunteers both tagged and geo-tagged each photo and video if they portrayed evidence of damage. Within 12 hours a dataset of 100 georeferenced images and videos were collected. It resulted in a very detailed crisis map shown in figure 2.3. This was the first official crisis-map based solely on social media content [(Meier, 2013b), p. 101]. In the aftermath of this crisis, an algorithm was developed to automatically detect tweets that link to photos and videos, but it doesn't mean that micro-tasking work is not important anymore.

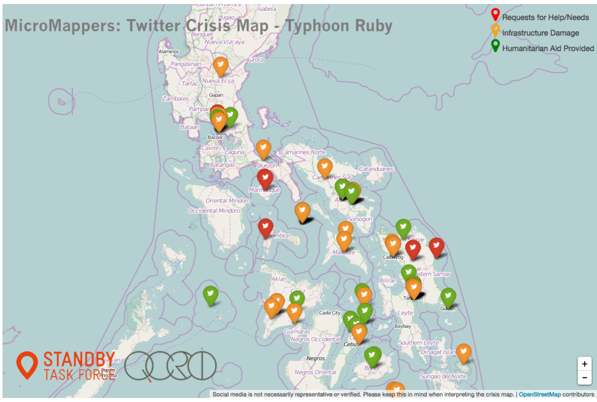


Figure 2.3: Typhoon Ruby Crisis map (Meier, 2014)

Micro-task crowdsourcing refers to a problem-solving model in which a problem or task is outsourced to a distributed group of people by splitting the task or problem into smaller sub-tasks or sub-problems. The sub-tasks or sub-problems are then solved by multiple workers independently, often in return for a reward (Sarasua et al., 2012). Thanks to micro-tasking platforms as Amazon's Mechanical Turk (MTurk; www.mturk.com), it is possible to build a hybrid human-machine system that combines the scalability of computers with the yet unmatched cognitive abilities of the human brain (Difallah et al., 2016). Gadiraju et al. (2015) findings when analyzing data from MTurk, indicate rapid growth in micro-task crowdsourcing. With the establishment of micro-task crowdsourcing platforms as MTurk and CrowdFlower (www.crowdflower.com), micro-tasking is much more accessible. Micro-tasking practitioners are actively turning towards paid crowdsourcing to solve data-centric tasks that require human input (Gadiraju et al., 2015). Most cases of micro-tasking combine human computation abilities with crowdsourcing.

In machine-learning algorithms, combining human computation abilities and crowdsourcing with fast machine learning algorithms has been a success. The team "Tomnod" [1] did a project in Australia where they combined human resources, crowdsourcing, and machine learning to locate swimming pools. The machine learning algorithm found polygons where there was likely to be a swimming pool. Then the users participating in finding the swimming pools were only shown polygons the algorithm had selected, minimizing the search area, shown in figure 2.4. This approach was used in order to reduce the number of user votes required to classify the pools but yet obtain a sufficient confidence (Kostas, 2016). This is a good example of micro-tasking. Instead of serving the users with satellite photos of huge areas, the photos was divided into polygons created by an algorithm. They then divided the task into smaller tasks, they micro-tasked the work. The resulting dataset was then used to train a swimming pool detecting convolutional neural network.

[1] Tomnod is a team of volunteers who work together to identify important objects and interesting places in satellite images; www.tomnod.com

Figure 2.4: Polygons created by an algorithm that maybe contain pools (Nikki, 2016)

Most cases of micro-tasking usage exploit the large volume capabilities machines have and the cognitive capabilities of humans (Difallah et al., 2016). Micro-tasking has also been used to process queries. In the Franklin et al. (2011) paper they extended a traditional query engine with a small number of operations that requires human input by generating and submitting requests. They used a micro-tasking platform to get the crowd to answer queries that cannot otherwise be answered. There are especially two cases where human input is needed: a) when the data is unknown or incomplete, b) when there is a need for subjective comparisons. They used auto-generated user interfaces and new query operators that can obtain human input via the interfaces. The Franklin et al. (2011) paper demonstrated that human input can be leveraged to dramatically extend the range of SQL-based query processing. People are good at comparing items, such as how well an image represents a particular concept. Humans are also good at finding relevant information with the help of search engines etc (Franklin et al., 2011). By utilizing these qualities in humans, like they did in (Franklin et al., 2011) paper by developing a micro-tasking based implementation of query operations, a huge cost and time sparing potential can be utilized.

One of the advantages of micro-tasking platforms like "Tomnod" and "CrowdFlower", that is mentioned by Meier (2013b) (p. 99), is the built-in quality control mechanisms that ensure a relatively high quality of output data. They set a review constraint, for instance in a project where they tagged satellite imagery of Somalia each unique image was reviewed by at least three different volunteers and only when all three agreed on type and location it was approved.

2.3.1 Micro-tasking workforce

It is said that crowdsourcing is radically changing the nature of work Deng et al. (2016). Traditional workers are restricted to offices and arranged office hours. With crowdsourcing, through for instance micro-tasking platforms, the workers can choose when to work, and even better: which jobs to perform. This appears very attractive, but is it only on the surface?

According to Deng et al. (2016), evidence indicates that crowdsourcing is radically changing people's perspectives on how to manage their work-life balance. Compared to "traditional" work tasks, the micro-tasks are simple and fast to finish (within a couple of minutes). The worker is also often compensated with tiny rewards every time they complete a micro-task. The workers are then rewarded often, which is motivating.

Individuals who perform micro-tasks for micropayment is called *crowd workers* by (Deng et al., 2016). A study done on workers in the micro-tasking platform MTurk (section 2.3.2.1), says that the workers are representative for the general Internet user population, but are generally younger and have lower incomes and smaller families (Ipeirotis and G., 2010).

2.3.2 Micro-tasking platforms

2.3.2.1 Amazon's Mechanical Turk

Amazon's Mechanical Turk (MTurk) is one of the biggest (if not the biggest) micro-tasking platform today. It provides the infrastructure, connectivity and payment mechanisms so that hundreds of thousands of people can perform micro-tasks on the Internet and get paid for it. MTurk is used for many different tasks that are easier for people than computers. It contains simple tasks such as labeling or segmenting images or tagging content, to more complex tasks such as translating or even editing text (**??**) (Franklin et al., 2011). In the marketplace, employers are known as requesters and they post tasks, called *human intelligence tasks* (HIT's). The HIT's are then picked up by online users, *crowd workers*, who complete the tasks in exchange for a small payment (a few cents per HIT) (Ipeirotis and G., 2010).

2.3.2.2 Tasking manager

The Tasking Manager tool is OpenStreetMap's micro-tasking platform. It was created in the aftermath of the Haiti earthquake in 2010 (Palen et al., 2015). The tool is used to coordinate satellite image tracing projects. The tool sorts the area covered by the satellite images into grids so that multiple people can map the same area at the same time. Each person works at one grid each, this way they don't map the same areas. This is an very effective approach to coordinate the crowd participating in the mapping. The tasking manager is mainly used by the *Humanitarian OpenStreetMap Team* (HOT). This platform do not have a rewarding system og a gamification approach. It is solely based on volunteer contributors. The page shows which areas need to be mapped and which areas need the mapping validated by others.

There are also other tools in OpenStreetMap. Tofix etcetc.

2.3.2.3 CrowdFlower

CrowdFlower is a company that wants to help businesses take advantage of crowdsourcing and/or human computation. They act as an intermediary for these businesses (Quinn and Bederson, 2011). CrowdFlower receives tasks from businesses wanting to crowdsource their work or problems. A project done for eBay exploited CrowdFlower's large online contributor pool and completed the tasks given to them from eBay five times faster than a traditional outsourcing team. eBay got a solution that was optimized for both quality and cost. CrowdFlower works with a variety of services to get connected with workers (i.e MTurk) (Quinn and Bederson, 2011).

What's special with CorwdFlower is their close ties with AI technology and a crowdsourced workforce. Their costumers are allowed to perform tasks with algorithms and machine learning, but bring in human judgement when they're not confident on the technology and the human work can make the algorithms smarter (Ha, 2016). Founder of CrowdFlower says that "self-driving cars have gotten pretty good at recognizing many of the objects they encounter on the street, [..] they can still struggle with tricky things like "a person in a Halloween costume dressed as a stationary object, or a pole with a person painted on it," which is where CrowdFlower comes in." (Ha, 2016).

2.3.3 Challenges

Getting enough people to use the micro-tasking platforms is crucial for its success. Most of the platforms mentioned in this chapter give payments to the workers. Another option is to make the platform as a game, which is also shown in this chapter. Creating a micro-tasking platform without payments or gamification factors the page is likely to have a short life, even though the tasking manager, supported by HOT, is an exception to this rule.

A problem when combining machines and humans is that machines can do their operations in real-time, while humans are unpredictable, they can come and go as they wish. This creates a gap where the micro-tasking platforms cannot guarantee on the task completion time (Difallah et al., 2016).

The human computation abilities can also be overestimated. During the classification of swimming pools in Australia, the Tomnod team faced some unexpected challenges. As described in section 2.3, they used the crowd to classify if a polygon contained a swimming pool or not, an algorithm had pointed out the polygons first. When reviewing a random sample from the result, they found an indication that 26% of polygons that contained a pool were identified as not containing pools by the crowd (Kostas, 2016). Further studies also showed that the guilty part was the crowd, the algorithm had correctly detected polygons containing pools. In a case where the algorithm was 85% confident that the polygon contained a pool, only one voted 'yes', six voted 'no, this polygon do not contain a pool'. The solution was to combine the human verdict with the machine's prediction. This example shows that it is important to use the right combination of humans and machines. Tasks that at first seems simple to do for humans, may be more challenging that expected. Basic object detection using machine learning perform very well when used together with human operations.

It is important that operations added to a micro-tasking platform consider the talents and limitations of human workers (Franklin et al., 2011) and this is what this thesis try to examine. What are the limitations of human workers when dealing with maps and geospatial data. It has been shown that crowds can be "programmed" to execute classical algorithms such as Quicksort, but such use of available resources is neither performant nor cost-efficient (Franklin et al., 2011).

3 Methodology and experiment

Gadiraju et al. (2015) categorize typically crowdsourced tasks into six top-level classes. Interesting classes within geospatial data is *Verification and validation*, *Interpretation and analysis* and *Content creation*. There are examples of all three task classes in geospatial crowdsourcing. During imports of large datasets into OpenStreetMap, crowdsourcing is used to validate the new data. In humanitarian OpenSteetMap, they map areas during a crisis to support the help organizations through crowdsourcing, creating valuable content to the workers in the field. In a machine learning process, they are starting to use micro-tasks to both validate the created data and also create test data sets to the algorithms. *Interpretation and analysis* tasks rely on the individual to use their interpretation skills during task completion. This is the task class used in this thesis during the survey. Is it safe to assume that individuals, both experienced and inexperienced, can interpret and analyse geospatial data presented to the on both map and in tables correctly? This is the main goal of the survey.

3.1 Survey

This thesis will try to determine questions regarding micro-tasks containing geospatial data. Little research is done on how well inexperienced individuals solve micro-tasks when they involve map interaction and geospatial data. To the authors best knowledge, little, if any, research has been done on micro-tasks involving map interaction and geospatial interpretation and analysis.

3.2 Experiment

The survey is a part of this thesis. The survey is used to answer different hypothesis around geospatial micro-tasks. To be able to answer the hypothesizes three tasks containing the same two questions was developed. The questions will represent two different micro-tasks involving geospatial data, while the three tasks will vary the number of elements the participant will use to answer the questions with. The participant will always answer the two question's on six elements, but the tasks vary how many element's need to be handled at the same time. The variation of a number of elements in the tasks is to hopefully find out if or how much the number of elements in a micro-task effect how well people solves the task.

When selecting the number of elements in the three different tasks the author decided to base this on cognitive load theory. Cognitive load theory refers to the total amount of mental effort being used in the working memory. Working memory is determined by the number of information elements that need to be processed simultaneously within a certain amount of time (Barrouillet et al., 2007). A heavy cognitive load can have negative effects on task completion, also the cognitive load that is imposed by a learning task is much higher for novices that for more advanced students (Leppink et al., 2014).

It is stated that the working memory has a limited capacity of seven plus or minus two elements (or chunks) of information when merely holding information and even fewer (ca four) when processing information (Leppink et al., 2014). By choosing three elements in one task and six elements in the other task this paper can determine if the theories about the limited capacity of the human brain also apply to maps and geospatial data. The last task will only contain one element as a minimum cognitive load task. This can help answer how many elements a human can process when doing micro-tasks containing geospatial data. The goal is to determine a preferred number of elements within a micro-task to use when developing micro-tasks so that they are most efficient and accurate.

The "magical" number of 4 has been demonstrated to limit much of human information processing (Mandler, 2013). It is said that polygon comparison demand medium cognitive load (Kiefer et al., 2016), which is what the participants do in the first question in this survey. Kiefer et al. (2016) argues that high cognitive load may lead to less effective map reading and spatial orientation, as well as decreased spatial learning. Since polygon comparison doesn't demand high cognitive load, the task should at least not be too demanding on the one element task and the three elements task. A worry is that the inexperienced participants will have a bigger struggle than the experienced participants. The extraneous cognitive load imposed high for the inexperienced when solving problems, because their lack of prior knowledge of how to solve that type of problem forces them to resort to weak problem-solving strategies (Leppink et al., 2014). By dividing the participants into experienced and inexperienced categories the results from the survey can help determine if geospatial micro-tasks are too demanding on inexperienced individuals.

The survey will then contain three tasks, each task contains six elements but the tasks vary how many elements the participant need to handle at the same time. One task will serve the participant with one and one element, the task that demands the smallest cognitive load. The other task will serve the participant with three and three elements at the same time. This number is just under the limit of how much information humans can process. The last task will serve the participant with all the elements at the same time. This number exceeds the human capacity when processing information according to Leppink et al. (2014).

There are two variable types used in this survey, dependent- and independent variables. The dependent variables are: time spent on each question and each task, the number of correctly chosen elements in both questions and also how difficult the participant though the task was. The independent variables are: number of elements in the task, experienced or inexperienced participant, gender, age and if the participant knows micro-tasking.

3.3 Determining the building shapes

Remote sensing is a tool or technique for extracting information about objects or geographic areas. All remote sensing images are subject to some form of geometric distortions. The distortions depend on how the data are obtained (Toutin, 2004). In Norway, most remote sensing images are analysed manually. This is also the case in OpenStreetMap. When using remotely sensed images to create for instance building footprints, it's important to be aware of the distortions in these images.

According to Fan et al. (2014), there was over 77 million buildings in the OpenStreetMap (OSM) database in 2013. A study of the geometries of building footprints in the city Munich reveal a large diversity in the geometries (Fan et al., 2014), and this is probably not the only city with this kind of diversity. To evaluate the quality of the building footprints in OSM, the Fan et al. (2014) paper used four criterion's, completeness, semantic accuracy, position accuracy and shape accuracy.

In the creation of the elements and conflicts used in the first question in the survey, the quality criterion's shape- and position accuracy were emphasized. The first question asks the participant to select the shape that fits the marked building on the map best. The goal is to create shapes that matches realistic cases that occur for instance in OSM.

Shape accuracy evaluates how well the layer matches the building with reference to an aerial image. Fan et al. (2014) mentions three main reasons to why building footprints are simplified in OSM. First reason is because of the difficulties following building details when looking from a bird's-eye view. Second reason is the limited resolution on the Bing aerial image used during digitalization. The last reason that is mentioned is that the volunteers in OSM don't have the patience to digitalize a complicated footprint exactly as it is. Drawing two layers with one of them matching the building shape better than the other, the participant has to use an aerial image to determine which layer fits the building best. This will test if the participants manage to make correct shape judgements by only using an aerial image as reference.

Position accuracy evaluates how well the coordinate value of a building relates to the reality on the ground. The correct layer will be drawn on the corresponding ground coordinates, while the conflicting layer will not match the ground. Fan et al. (2014) tested the accuracy of buildings in OSM, and concluded with an mean offset of 4.13 m. The low positional accuracy of OSM building footprints data is caused by the limited resolution of Bing map images. By combining shape- and position accuracy in some of the cases used in question one this study can also determine if participants manage to evaluate both factors. In this study the participants don't have available information about what the true ground coordinates are. Therefore position accuracy will be examined by shifting one of the layers. The correct positional accuracy will be at the building in the aerial image.

3.4 Web application

This thesis used an online web-based survey to conduct the experiment. An online survey avoid the cost and effort of printing, distributing, and collecting paper forms. Many people prefer to answer a brief survey displayed on a screen instead of filling in and returning a printed form (Ben and Plaisant, 2009).

In a self selected sample, which is some the case here, there is potentially a bias in the sample (Ben and Plaisant, 2009).

3.4.1 Technology

React
Django
Postgis
AWS

3.4.2 Architecture

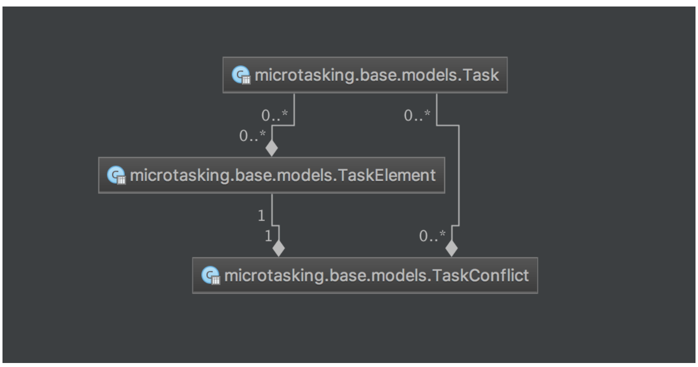


Figure 3.1: UML diagram, Task: Task Element and Task Conflict

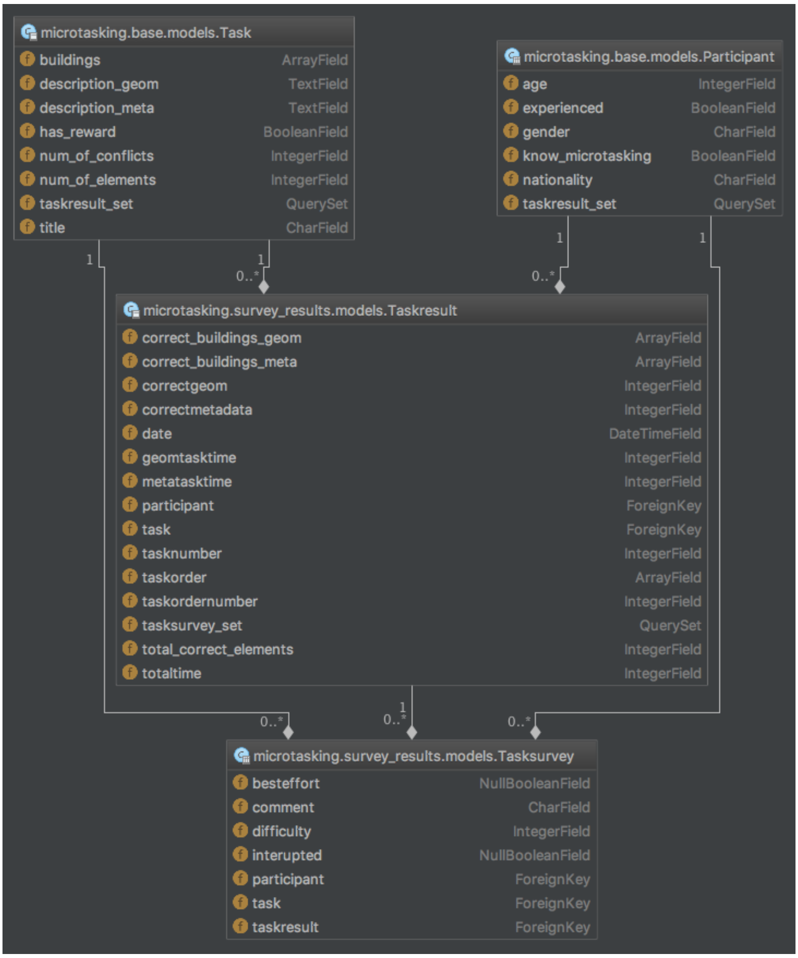


Figure 3.2: UML diagram, Survey result: Task result and Task survey

3.4.3 Graphical Interface

3.5 Pilot test

It is important to pilot test the survey prior to actual use (Ben and Plaisant, 2009). A pilot test provides an opportunity to validate the wording of the tasks, do the participants understand the tasks? It also helps understand the time necessary for completing the survey, which should be communicated to the participants in prior to the survey (Schade, 2015). The pilot-test will be conducted with a small sample of users. Results from the pilot test are in this thesis used to do improvements to the actual survey, to the web application hosting the survey and to find errors or weaknesses in the database models.

After the pilot test, the usability was measured. The standard ISO 9241-11 suggests that measures of usability should cover effectiveness, efficiency and satisfaction (ISO, 1998). Measuring these three classes of metric can vary widely and makes it difficult to make comparisons of usability between different systems. "[...] just because a particular design feature has proved to be very useful in making one system usable does not necessarily mean that it will do so for another system" (Brooke, 1996). Usability in this thesis will be measured with the *System Usability Scale*(SUS) because it gives a subjective measure of usability. The *System Usability Scale* questionnaire consists of ten statements where the participants rate their agreement on a five-point scale (Ben and Plaisant, 2009). Subjective measure of usability is usually obtained through the use of questionnaire and attitude scales (Brooke, 1996). SUS was developed to be quick and simple, but also reliable enough to be able to compare performance changes between versions (Brooke, 1996). It is also easy to administer the participants through the usability test and it can be used on small sample sizes and still give reliable results (Affairs, 2013).

The usability is important to measure. If the participants don't understand how the web application works, they will probably not do the survey since they then have to invest time in understanding what to do. It is also important to get enough participants to do the whole survey and not quit halfway in frustration of not understanding it properly. The *System Usability Scale* can effectively differentiate between usable and unusable systems (Affairs, 2013).

3.5.1 Execution of the pilot test

The pilot test was conducted with a total of eight participants, five experienced and three non-experienced participants aged from 22 to 64 years. It started with a brief information about this study and the survey. They were told to talk out load during the survey, no help or guidance was given to the participants. The author observed the participants while they conducted the survey. The author took notes and watched if the participants understood the questions in the survey correctly. After the survey a *System Usability Scale* questionnaire was answered by the participants. At the end, the participants were asked to give general feedback on the web application. The SUS score and the feedback were then used to determine the usability of the web application and to determine which improvements to be done.

3.5.2 Results from the pilot test

- Did someone knew micro-tasking? Can we see something here?

The average SUS score was 84.64 out of 100. Anything above 68 is considered above average (Affairs, 2013). When adding the SUS score to an adjective rating will an score of 85.5 or higher be described as excellent (Bangor et al., 2009). A score of 84.64 is then described as good/excellent. This result gives a good indication that the web-application is user friendly.

All participants thought that the instruction movie was confusing. It was short, the instructions went too fast and it lacked voice descriptions. The movie needed major improvements, an important discovery. The purpose of the movie is to give the participant an introduction to how to answer the two questions. It gives important instructions, especially for participants that are not used to working with maps on a web page.

Overall feedback on question one was that it was difficult to understand which building was which and also when a building layer was selected or not. The lack of labels on the buildings was done on purpose to get the task as much as possible realistic. The process of selecting the best building layer needed improvements, it had to be clearer that selection was done by clicking on the layer on the map, not by using the layer control as some thought. This problem was added to the movie with voice description, describing in detail how a layer was selected. The design on the question one page was also improved by adding color to the text telling the participant which layer they had selected.

Another feedback from one of the participants was that both question views had too much information and long sentences. The participant advised to shorten the sentences and to move some of the information to the movie. This request was fulfilled in the new movie. The task progress bar was also removed, during the eight pilot tests the author didn't notice that any of the participants looked at the task progress bar. The progress bar was thought of as an extra help to inform how many elements was left in the task. Only the survey progress bar on the top right was found necessary.

The pilot test data was used to test some of the hypothesis to find errors or weaknesses in the databasemodel. The data was extracted with the help of Django QuerySets and saved in csv files. Some preliminary results can be seen in section 3.5.3. There were a few errors and weaknesses found during the statistical tests. Changes to the database models was necessary, and the changes done are listed under:

1. Add foreign key from TaskResult model to TaskSurvey
2. Added four other fields in TaskResult model
    - Total correct elements
    - Task order
    - Task number
    - List of correctly chosen building numbers in both questions
3. Difficulty field in Tasksurvey model was changed from Char field to Integer field

The additional fields will mainly help with creating plots to better interpret the data and to more easily visualize the different results.

3.5.3 Preliminary results

The pilot-test data was not normally distributed, and doing statistical analysis on data from eight participants didn't seem relevant. The data was mapped in char plots, visualizing some trends.

The two oldest participants spent almost twice as much time on the test than the younger. Maybe it was too much cognitive load on them. Learning a new application and at the same time understanding how to do the survey and answer the questions given to them. One of them were experienced and the other inexperienced, so this is a surprising result. Figure 3.3 show the task results from all participants ordered by age. There are three entries per participant, so three and three bars are results from the same participant. Task 1 represents the task with one elements, task 2 the task with three elements and task 3 the task with six elements.

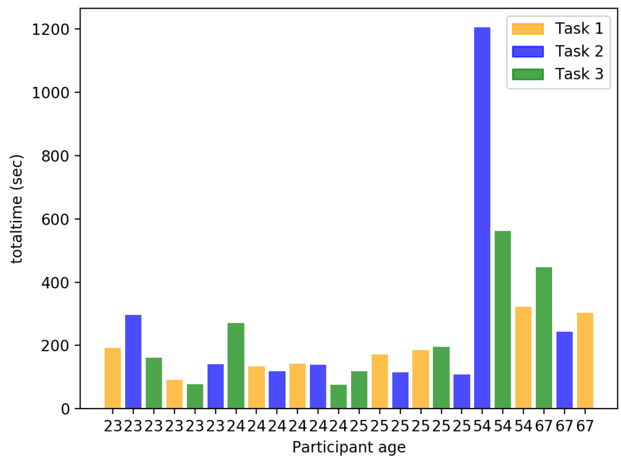
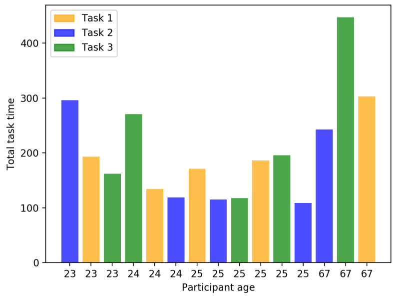
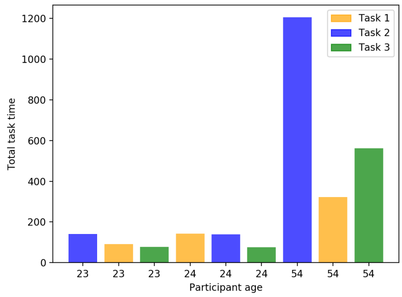


Figure 3.3: Total time - all participants ordered by age

Splitting the data into two groups, experienced and inexperienced, and then mapping totaltime and order by age plots can be seen in figures 3.4a and 3.4b. Experienced participant had a mean time of 3 minutes and 24 seconds (204 sec) and inexperienced participants had a mean time of 5 minutes and 4 seconds (304 sec), almost 2 minutes difference. It is clear to see that the 54 year old participant's total time on task 2 is dramatically higher than the rest. By looking at figure 3.4b, two of the inexperienced participants spent less than 200 seconds on all their tasks.



(a) Experienced: Mean 204 sec



(b) Inexperienced: Mean 304 sec

Figure 3.4: Total time - ordered by age, splitted into experienced and inexperienced

The average time spent on the survey was 18 minutes. The two oldest participants used on average 33 minutes, while the rest of the participants spent on average 13 minutes to complete the survey.

In the pilot-test the same building layers and meta data rows was used in all three tasks. At the end of the pilot-test the author asked the participants if they remembered the buildings and meta information in the last task. $\frac{7}{8}$ answered yes on the question. This information was important. If every participant does a better job at the last task the result will not be as useful. Even though the task order varies. Reading the data in figure 3.3, $\frac{6}{8}$ participants spent less time on the last task, even though the task order varied. This matches the number of participants who remembered the buildings and meta information from the previous tasks.

Total number of correctly chosen elements in each task is shown in figure 3.5.

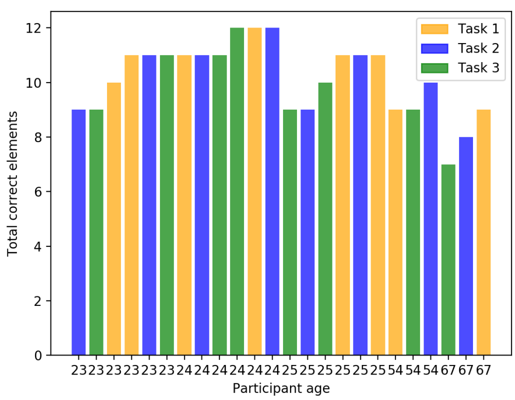
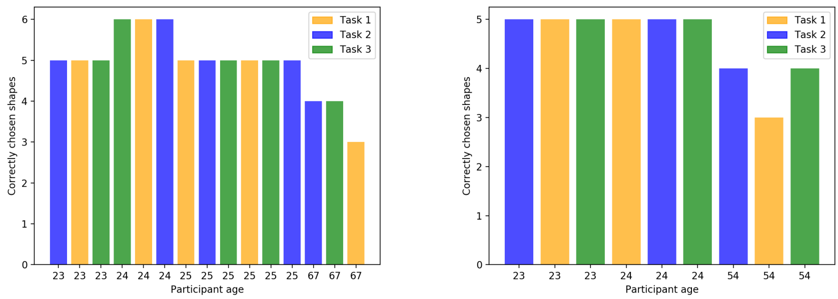


Figure 3.5: Total correct, both questions - ordered by age



(a) Experienced (b) Inexperienced

Figure 3.6: Number of correctly chosen building shapes - splitted by experience

3.6 Determining the sample size

The sample size is influenced by a number of factors, including the purpose of the study, population size, the risk of selecting a "bad" sample and the allowable sampling error (Israel, 1992). In this survey there are three possible ways of determining the sample size.

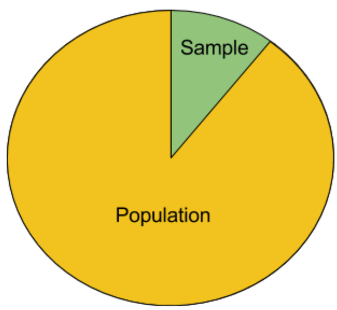


Figure 3.7: Population vs. sample

A sample is a collection of observations and is the subset of a population, illustrated in figure 3.7. The population size in this survey is not easily determined. A population is the collection of individuals of a particular type (Walpole et al., 2012). All individuals with access to a computer and internet interested in contributing to micro-tasks is basicly the population.

There are three possible ways of determining the sample size in this study. The first option is to use a sample size from a similar study. The risk is to repeat errors that were made in determining the sample for another study. The second option is to rely on published tables, depending on precision, confidence levels, and variability. According to Israel (1992) table 1, a precision of 0.05, confidence level of 95% and a size of population greater than 100'000, the necessary sample size is 400. If the precision is changed to 0.1, the sample size necessary increases to 100 (Israel, 1992). The numbers found in the table reflects the number of obtained responses. The last approach is to use formulas to calculate the sample size. The formulas requires the standard deviation and how much variance to expect in the response (Smith, 2013)(Israel, 1992). Israel (1992) mentions that the table gives a useful guide for determining the sample size, and that formulas are used if the study has a different combination of precision and confidence. This study will use the table result since the combinations matches this study.

It's important to mention that the quality of the sample is as important as it's size. The more variable the sampled data is, the larger the sample size is required (Israel, 1992). It's also desirable to choose a random sample, which means that the observations are made independently and random. The main purpose of using a random sample is to obtain correct information about the unknown population parameters (Walpole et al., 2012).

4 | Result

4.1 Sample data from Survey

Independence of observations. This is mostly a study design issue and, as such, you will need to determine whether you believe it is possible that your observations are not independent based on your study design (e.g., group work/families/etc). A lack of independence of cases has been stated as the most serious assumption to fail. Often, there is little you can do that offers a good solution to this problem.

Designed the survey so that the observations should be random and independent
- Random order on the tests
- Random color on the layers
- Random which order the layers was drawn on the map
- Random which order the metadata was written in the table

4.2 Statistics theory

This section will give an introduction to the statistics used in this thesis. The thesis will examine the data with parametric methods but also with non-parametric methods if the assumption of a normally distributed samples fails. A nonparametric method is much more efficient than the parametric procedure when the set of data used in the test deviates significantly from the normal distribution (Walpole et al., 2012). There are also some disadvantages using nonparametric methods. The methods will be less efficient, and to acchieve the same power as the corresponding parametric method a larger sample size is required. If parametric and nonparametric tests are both valid on the same set of data, the parametric test should be used (Walpole et al., 2012).

4.2.1 Normal testing

The sampling distribution of a statistic depend on the distribution of the population, the size of the samples, and the method of choosing the samples (Walpole et al., 2012). Sampling distibution describes the variability of sample averages around the population mean μ. All parametric statistics assumes normally distributed, independent observations. Parametric tests are preffered in statistics because it got more statistical power than nonparametric tests (Frost, 2015). The power of a test is the probability of correctly rejecting a false null hypothesis, which in this case is the ability to detect if the sample comes from a non-normal distribution. To determine if a sample is normally distrubuted there exists both visual methods and normality tests to assess the samples normality. A visual inspection of the sample's distribution is usually unreliable and does not guarantee that the distribution is normal (Pearson et al., 2006). Presenting the data visually gives the reader an opportunity to judge the distribution themselves. In this thesis histograms are used to visualize the data for normality.

Normality tests compare the scores in the sample to a normally distributed set of scores with the same mean and standard deviation (Ghasemi and Zahediasl, 2012). There are multiple normality tests, and deciding which test to use is not easy. This study needs a test that doesn't require every value to be unique, a test that can handle ties (identical observations). The survey used to collect the samples in this study do not guarantee unique values.

The D'Agostino-Pearson omnibus test stand out as the best choice. This test first computes the skewness, see figure 4.1, and kurtois, see figure 4.2, to quantify how far from the normal distribution the sample is from the terms of assymetry and shape. Then it calculates how far each of these values differs from the value expected with a normal distribution (Pearson et al., 2006). It works well even if all values are not unique (Motulsky, 2013). The test also works well on both short- and long-tailed distributions (Yap and Sim, 2011).

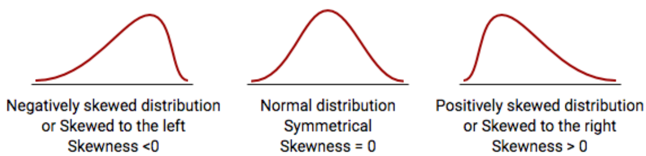


Figure 4.1: Skew (MedCalc Software bvba, 2017)

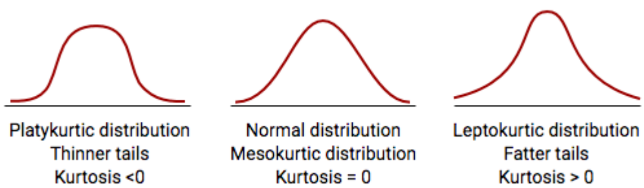


Figure 4.2: Kurtois (MedCalc Software bvba, 2017)

The D'Agostino-Pearson test uses the following hypothesis:

$$H_0\text{: The data follows the normal distribution}$$
$$H_A\text{: The data do not follow the normal distribution}$$

For small sample sizes, normality tests have little power to reject the null hypothesis, therefore small sample sizes most often pass normality tests. For large sample sizes, significant results would be derived even in the case of a small deviation from normality (Pearson et al., 2006). When the null hypothesis cannot be rejected, then there are two possible cases. First case is to accept the null hypothesis or the second case is that the sample size is not large enough to either accept or reject the null hypothesis (The Pennsylvania State University, 2017). An acceptance of the null hypothesis implies that the evidence was insufficient, the result does not necessary accept H_0, but fails to reject H_0 (Walpole et al., 2012).

4.2.2 Bionomal disstibution

Used for discrete variables. It used the probability of getting x successes and $n - x$ failures in n trials. Each success comes with a probability p and each failure with probability $q = 1 - p$ [(Walpole et al., 2012), p. 145]. The sample mean $\overline{x}$ and variance of $\overline{x}$ of the bionomial distribution is: $\overline{x} = n * p$ and $\sigma^2 = n * p * q$. The probability p has to be the same on every trial - NOT TRUE HERE.

In the survey, the number of correctly chosen elements is recorded. Here x = the number of correct elements. x is a random variable who has the binomial distribution. The following null and alternative hypothesis can be used:

H_0: All elements are correctly chosen in each task
H_A: Not all element are correctly chosen in each task

$p = \frac{\overline{x}}{n}$, if $p*n >= 5$ and $n*(1-p) >= 5$ then we can use the normal distribution.

4.2.3 Hypothesis testing

The null- and alternative hypothesis are statements regarding a difference or an effect that occur in the population of the study. The alternative hypothesis (Ha) usually represents the question to be answered or the theory to be tested, while the null hypothesis (H_0) nullifies or opposes Ha (Walpole et al., 2012). The sample collected in the study is used to test which statement is most likely (technically it's testing the evidence against the null hypothesis). When the hypothesis is identified, both null and alternative, the next step is to find evidence and develop a strategy for or against the null hypothesis (Lund Research Ltd, 2013a).

The first step, after identifying the hypothesis, is to determine the level of statistical significance, often expressed as the *p-value*. A statistical test will result in the probability (*the p-value*) of observing your sample results given that the null hypothesis is true. A significance level widely used in academic research is 0.05 or 0.01 (Walpole et al., 2012).

You should not report the result as "significant difference", but instead report it as "statistically significant difference". This is because your decision as to whether the result is significant or not should not be based solely on your statistical test. Therefore, to indicate to readers that this "significance" is a statistical one, include this is your sentence (Lund Research Ltd, 2013b).

4.2.3.1 Two sample t-test

When estimating the difference between two means a two-sample t-test is used (Walpole et al., 2012). A two sampled test assumes two independent, random samples from distributions with means [μ_1 , μ_2] and variances [σ_1^2, σ_2^2]. The hypothesis on two means can be written as:

$$H_0\text{: } \mu_1 \text{ - } \mu_2 = 0 \text{ or } \mu_1 = \mu_2$$
$$H_A\text{: } \mu_1 \text{ - } \mu_2 > 0 \text{ or } \mu_1 > \mu_1$$

Then the hypothesis refer to a one-tailed two sampled t-test. Before doing tests on the two means, the Levene's Test is used to test if the samples are from populations with equal variances. It tests the hypothesis:

H_0: Input samples are from populations with equal variances
H_A: Input samples are from populations that do not have equal variances

If we can assume equal variances in the two samples and the samples are normal distributed, a two-sampled t-test may be used.

Because the one-sided tests can be backed out from the two-sided tests. (With symmetric distributions one-sided p-value is just half of the two-sided pvalue). It goes on to say that scipy always gives the test statistic as signed. This means that given p and t values from a two-tailed test, you would reject the null hypothesis of a greater-than test when p/2 < alpha and t > 0, and of a less-than test when p/2 < alpha and t < 0.

Relevant hypothesis in this study that can be tested with a two-sampled t-test (if the conditions mentioned above are valid) is listed under.

Hypothesis - Two sample t-test

H_0**:** Mean task time between participants are equal
H_A**:** Experienced participants finish the tasks faster, use less time

H_0: Total number of correct elements between participants are equal
H_A: Experienced participants have a higher number of correct elements

H_0: There are no difference in total number of correct elements between the tasks
H_A: Participants have more correct elements on the one element task

H_0: There are no difference in mean time between the tasks
H_A: Participants finish the one element task faster

Before solving the hypothesis the conditions needs to be testet. More on this later.

4.2.3.2 Analysis-of-Variance

Analysis-of-Variance (*ANOVA*) is according to Walpole et al. (2012) a very common procedure used for testing population means. Where a two sample t-test are restricted to consider no more than two population parameters, *ANOVA* can test multiple population parameters. A part of the goal of *ANOVA* is to determine if the differences among the means of two or more samples are what we would expect due to random variation alone, or due to variation beyond merely random effects. *ANOVA* assumes normally distributed, independent, samples with equal variance. The equal variance assumtion will be tested with Levene's Test also mentioned in subsection 4.2.3.1.

One-way *ANOVA* tests the null hypothesis that two or more groups have the same population mean given that the mean is measured on the same factor or variable in all groups(Lund Research Ltd, 2013b). The hypothesis test can be written like this:

$$H_0\colon\ \mu_1 = \mu_2 = ... = \mu_k$$
$$H_A\colon \text{ At least two of the means are different}$$

μ equals the group mean and k represents the number of groups. It is important to check that each group are normally distributed, not only the sample (Lund Research Ltd, 2013b). The weakness of one-way *ANOVA* is that it cannot tell which specific groups were significally different from each other if H_0 is rejected. To be able to determine which group a *post hoc test* is used.

In an one-way *ANOVA* test there should be one variable and minimum three independent groups, which is an relevant approach considering the data produced from this thesis survey. There are at least two variables in the survey data, task time and number of correctly chosen elements. The survey result can be divided into three groups, one element task, three elements task and six elements task. Each entry in the sample should only be assigned to one group. Relevant hypothesis from the study that can be used in an one-way *ANOVA* test is shown under.

Hypothesis - One-way ANOVA

H_0: Mean task time is not different between the three tasks
H_A: Mean task time is different between at least two of the tasks
Variable = time, group = tasks

H_0: Total number of correct elements between the three tasks are equal
H_A: Total number of correct elements between at least two of the tasks are not equal
Variable = Number of correct elements, group = tasks

The hypothesis written above will be testen in the section blabla.

4.2.3.3 Wilcoxon Rank-Sum test

The Wilcoxon Rank-Sum test is an appropriate alternative to the two-sample t-test (see subsection 4.2.3.1) when the normality assuptions do not hold, but the samples are still independend and have a continous distribution (Walpole et al., 2012). Since this method is nonparametric (or distribution-free) it do not require the assumption of normality.

The hypothesis for Wilcoxon Rank-Sum Test is:

$$H_0\colon\ \tilde{\mu}_1 = \tilde{\mu}_2$$
$$H_A\colon\ \tilde{\mu}_1 > \tilde{\mu}_2 \text{ or } \tilde{\mu}_1 < \tilde{\mu}_2 \text{ or } \tilde{\mu}_1 \neq \tilde{\mu}_2$$

The alternative hypothesis depends on what the test should determine. If the sample with mean $\tilde{\mu}_1$ is greater than, smaller than or unequal to the sample with mean $\tilde{\mu}_2$. First select a random sample from each population with means $\tilde{\mu}_1$ and $\tilde{\mu}_2$. If the sample sizes are different, let n_1 be the number of observations in the smallest sample and n_2 for the largest sample. Then $\tilde{\mu}_1$ will be the mean for the smallest sample. If there are ties (identical observations) in the sample a Mann-Whitey U test is preffered (The Scipy community, 2017).

4.2.3.4 Mann-Whitey U test

Skriv om nødvendig, om vi bare bruker tid er det liten sannsynlighet at det et identiske målinger..

4.2.3.5 Kruskal-Wallis test

The Kruskal-Wallis test is a nonparametric alternative to one-way $ANOVA$ (see subsection 4.2.3.2) (Walpole et al., 2012). This test should be used if the assumption of normal distribution failed. As mentioned in this sections introduction, a nonparametric method does not assume normality. This test is an generalization of the rank-sum test when there are more than 2 samples.

Kruskal-Wallis is used to test equality of means in one-way $ANOVA$, so the hypothesis for the Kruskal-Wallis test is:

$$H_0\colon\ \mu_1 = \mu_2 = ... = \mu_k$$
$$H_A\colon \text{ Minimum two of the } \mu_k\text{'s are different}$$

Here μ_k is the rank mean for the group k. As in Wilcoxon Rank-Sum test (subsection 4.2.3.3), the number of observations in the smallest sample is assigned to n_1, the second smallest to n_2 and the largest sample is assigned to n_k.

4.3 Survey results

- All participants ordered by age
- All participants ordered by age, excluded by task 4
- All results in one task, ordered by age
- Average time per micro-task
- Is there a difference in task order number 1, 2, 3? time and correct
- Is there a difference in task number 1, 2, 3? time and correct

Can use it to explain the data

4.3.1 Gathered data

The gathered data will be analyse on the two variables: 1) total time used to complete each task and 2) number of correctly chosen elements per task. Total time and number of correct elements adds time and correctly chosen elements on question one and question two together. Sample mean $\overline{x}$, standard deviation of $\overline{x}$, standard error $(\frac{standarddeviation}{\sqrt{samplesize}})$ of $\overline{x}$, minimum in sample and maximum in sample are listed in the tables. In these tables, results from the training task is removed. Only results from the three tasks is used. Maximum possible correct elements per task is twelve. There are six elements in question one and six elements in question two, and the number of correctly chosen elements in each task is added together, maximum twelve correctly chosen elements.

The tables in this section, (4.3.1), are task results from all participants and all three tasks, excluding the training task. Task results with total time longer than 2160 seconds are filtered out. This is to remove 4 outliers that spend more than twice the approximated time (average time on the survey was 1080 seconds in the pilot test). These 4 participants also answered that they were disturbed during the test.

The samples are in the first subsection (4.3.1.1) divided into experienced and inexperienced, but the three tasks are not separated in this sample. In subsection 4.3.1.2 the sample are separated into the three tasks, all participants are kept in the sample. Section 4.3.1.3 and 4.3.1.4 separates the samples in the three tasks and also in experienced and inexperienced participants.

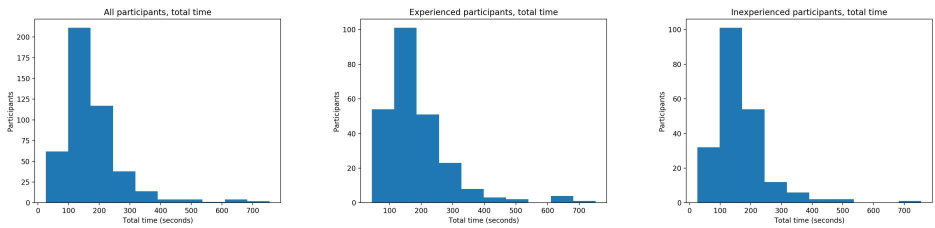
Removed all participants that said they was distracted. 26 task results was removed, 10 inexperienced and 18 experienced results.

4.3.1.1 All, experienced and inexperienced participants

The mean, standard deviation, minimum and maximum values are listen i table 4.1 and 4.2. I.

Total time per task (seconds)	All	Experienced	Inexperienced
Number of observations	429	229	200
Sample mean $\overline{x}$	170.32	177.65	161.94
Standard deviation of $\overline{x}$	82.19	88.24	73.99
Standard error of $\overline{x}$	3.98	5.83	5.23
Minimum in sample	38.00	52.00	38.00
Maximum in sample	657.00	657.00	529.00

Table 4.1: Total time (*4 entries per volunteer)*

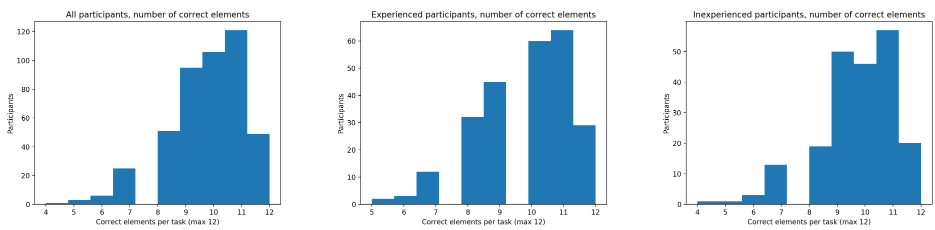


(a) All (b) Experienced (c) Inexperienced

Figure 4.3: Total time per task divided in all-, experienced- and inexperienced-participants

Correct elements per task	All	Experienced	Inexperienced
Number of observations	429	229	200
Sample mean $\overline{x}$	9.82	9.81	9.83
Standard deviation of $\overline{x}$	1.52	1.53	1.51
Standard error of $\overline{x}$	0.07	0.10	0.11
Minimum in sample	4.00	5.00	4.00
Maximum in sample	12.00	12.00	12.00

Table 4.2: Number of correctly chosen elements (*4 entries per volunteer)*



(a) All (b) Experienced (c) Inexperienced

Figure 4.4: Correctly chosen elements per task divided in all-, experienced- and inexperienced-participants

4.3.1.2 All participants, divided in task 1, task 2 and task 3

In table 4.3 and 4.4 mean, standard deviation, minimum and maximum is listed for the three different task the participants did in the survey. Task 1 is the task that served the participants with one and one elements. Task 2 is the task that served the participants with three and three elements, and task 3 gave all six elements at the same time.

Total time per task (seconds)	One element task	Three elements task	Six elements task
Number of observations	146	142	141
Sample mean $\overline{x}$	166.38	172.25	172.48
Standard deviation of $\overline{x}$	84.57	84.21	77.95
Standard error of $\overline{x}$	7.00	7.07	6.56
Minimum in sample	47	50	38
Maximum in sample	657	492	529

Table 4.3: Total time divided into task 1, task 2 and task 3

Correct elements per task	One element task	Three elements task	Six elements task
Number of observations	146	142	141
Sample mean $\overline{x}$	10.19	9.71	9.55
Standard deviation of $\overline{x}$	1.43	1.53	1.52
Standard error of $\overline{x}$	0.12	0.13	0.13
Minimum in sample	5.00	5.00	4.00
Maximum in sample	12.00	12.00	12.00

Table 4.4: Number of correctly chosen elements divided into task 1, task 2 and task 3

4.3.1.3 Experienced participants, divided in task 1, task 2 and task 3

Dividing task 1, task 2 and task 3 results into experienced and inexperienced. Table 4.5 are data gathered about experienced participants total time per task. Table 4.6 are data gathered about experienced participants number of correctly chosen elements per task.

Total time per task	One element task	Three elements task	Six elements task
Number of observations	81	84	82
Sample mean $\overline{x}$	187.74	174.65	191.93
Standard deviation of $\overline{x}$	122.08	84.30	115.18
Standard error of $\overline{x}$	13.64	9.20	12.79
Minimum in sample	57.00	52.00	44.00
Maximum in sample	657.00	492.00	752.00

Table 4.5: Experienced total time per task, divided by task

Correct elements per task	One element task	Three elements task	Six elements task
Number of observations	81	84	82
Sample mean $\overline{x}$	10.23	9.69	9.51
Standard deviation of $\overline{x}$	1.30	1.62	1.46
Standard error of $\overline{x}$	0.14	0.18	0.16
Minimum in sample	7.00	5.00	5.00
Maximum in sample	12.00	12.00	12.00

Table 4.6: Experienced participant's number of correct elements per task, divided by task

4.3.1.4 Inexperienced participants, divided in task 1, task 2 and task 3

Table 4.7 are mean time, standard deviation, minimum time and maximum time spent on each task for inexperienced participants. Number of correctly chosen elements per task for inexperienced participants is shown in table 4.8.

Total time per task (seconds)	One element task	Three elements task	Six elements task
Number of observations	71	69	70
Sample mean $\overline{x}$	159.28	174.42	169.50
Standard deviation of $\overline{x}$	68.24	106.69	83.17
Standard error of $\overline{x}$	8.10	12.84	9.94
Minimum in sample	47.00	26.00	38.00
Maximum in sample	487.00	755.00	529.00

Table 4.7: Inexperienced participant's time spent per task, divided by task

Correct elements per task	One element task	Three elements task	Six elements task
Number of observations	71	69	70
Sample mean $\overline{x}$	9.99	9.65	9.60
Standard deviation of $\overline{x}$	1.50	1.45	1.56
Standard error of $\overline{x}$	0.18	0.17	0.19
Minimum in sample	5.00	6.00	4.00
Maximum in sample	12.00	12.00	12.00

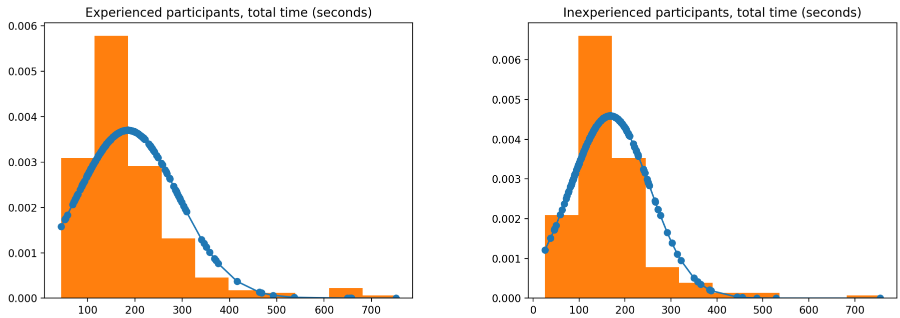
Table 4.8: Inexperienced participant's number of correct elements per task, divided by task

4.3.2 Normality tests

To check if a two-sample t-test (subsection 4.2.3.1) and *ANOVA*-test (subsection 4.2.3.2) can be used, the samples need to be tested if they are normally distributed or not. Both tests assume normally distributed samples. The normality section 4.2.1 concluded that the D'Agostino and Person normality test should be used in this thesis. A visual interpretation of histograms will also be a part of the normality tests.

4.3.2.1 Experienced and inexperienced participants - total time samples

The histograms 4.5a and 4.5b are positively skewed (see figure 4.1). This gives a strong evidence that the samples are not normally distributed. Samples involving time measurements are rarely normally distributed. This is because the sample will always be skewed since it is impossible to have negative time. There will always be a limit to how fast a participant can finish the tasks.



(a) Sample 1 - Experienced participants, total time

(b) Sample 2 - Inexperienced participants, total time

Figure 4.5: Histograms with normal distribution fit

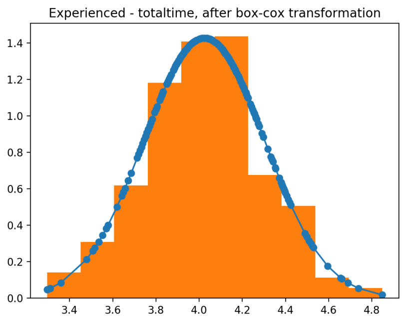
An D'Agostino and Pearson normality test (4.2.1) confirmed the visual assessment conclusion with an significance level of 5% (0.05). Both samples are not normally distributed with a confidence level of 95%.

D'Agostino and Pearson normality test
Significance level: 5%

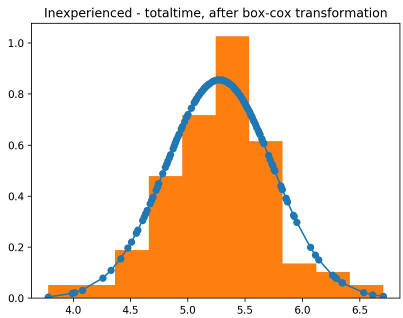
Sample 1: Experienced, total time per task
P-value: $3.874 * 10^{-22}$
The p-value is lower than the significance level (0.05), the null hypothesis is rejected and H_1 accepted.

Sample 2: Inexperienced, total time per task
P-value: $2.574 * 10^{-21}$
The p-value is lower than the significance level (0.05), the null hypothesis is rejected and H_1 accepted.

In both sample 1 and 2, the p-value was significantly lower than the significance level of 0.05. Data transformations are commonly used tools to improve normality of a sample distributions, but there are many types of data transformations. Osborne (2010) claim that almost all analyses, even nonparametric tests, benefit from improving the normality of the samples, especially when the normality test is significantly denied. Common traditional transformations are square root, inverse or converting to logarithmic scales (Osborne, 2010). A Box-Cox power transformation is used in this thesis. This transformation can be used on positive data. Box-Cox takes the idea of having a range of power transformations (square root $x^{\frac{1}{2}}$, inverse x^{-1} etc.) available to improve the effectiveness of normalizing and variance equalizing for both positively- and negatively-skewed variables (Osborne, 2010). This transformation will always use the appropriate transformation to be maximally effective in moving each sampled data towards normality. This is the reason why this thesis will use the Box-Cox transformation to hopefully achieve normal distributed samples.



(a) Sample 1 - Experienced participants



(b) Sample 2 - Inexperienced participants

Figure 4.6: Histograms with normal distribution fit after Box-Cox transformation

D'Agostino and Pearson normality test
(After Box-Cox transformation)
Significance level: 5%

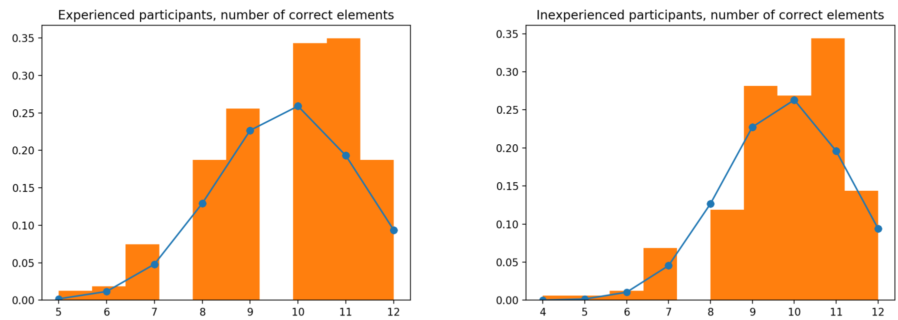
Sample 1: Experienced, total time per task
P-value: 0.849
The p-value is higher than the significance level (0.05), the null hypothesis is accepted.

Sample 2: Inexperienced, total time per task
P-value: 0.0623
The p-value is higher than the significance level (0.05), the null hypothesis is accepted.

The assumption that sample 1 and sample 2 are normally distributed is now accepted and can be used in parametric methods as two sample t-test and *ANOVA*.

4.3.2.2 Experienced and inexperienced participants - number of correctly chosen elements samples

Visual inspection of histogram 4.7a and 4.7b gives a good indication that sample 3 and 4 are not normally distributed. Both are negatively skewed (see figure 4.1).



(a) Sample 3 - Experienced participants

(b) Sample 4 - Inexperienced participants

Figure 4.7: Histograms with normal distribution fit - number of correctly chosen elements per task

D'Agostino and Pearson normality test confirm ou visual interpretation. Both samples accept the alternative hypothesis with p-values lower than the significant level 0.05.

D'Agostino and Pearson normality test
Significance level: 5%

Sample 1: Experienced, correct elements per task
P-value: 0.00443
The p-value is lower than the significance level (0.05), the null hypothesis is rejected and H_1 accepted.

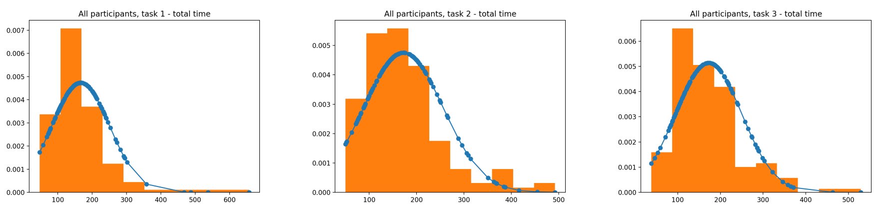
Sample 2: Inexperienced, correct elements per task
P-value: 0.00013
The p-value is lower than the significance level (0.05), the null hypothesis is rejected and H_1 accepted.

Sample 3 and 4 was then Box-Cox transformed. After transformation a new D'Agostino and Pearson normality test was done. Both samples also failed this test. Sample 3 and 4 are not normally distributed and need to be tested with non-parametric methods.

4.3.2.3 All participants - Task 1, Task 2 and Task 3 - total time per task

In this section the data is separated in the three tasks the participants did. It resulted in three samples: Sample 5, 6 and 7. These samples will be used to test weather there are an significant difference between the three tasks. First the samples will be normality tested.

Visual analysis of the three histograms in figure 4.8a, 4.8b and 4.8c show a positive skewness as the time histograms in section 4.3.2.1. This is evidence that the samples are not normally distributed.



(a) Sample 5 - Task 1 (b) Sample 6 - Task 2 (c) Sample 7 - Task 3

Figure 4.8: Histogram with normal distribution fit - sample with total time per task

The D'Agostino and Pearson normality test agreed with the visual analysis. P-values for all samples are smaller than the significance level 0.05, and the null hypothesis is rejected. The samples are not normally distributed.

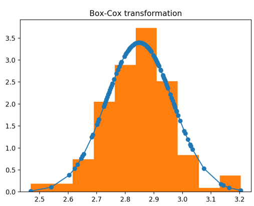
D'Agostino and Pearson normality test
Significance level: 5%

Sample 5: All, total time on task 1
P-value: $2.39 * 10^{-24}$
The p-value is lower than the significance level (0.05), the null hypothesis is rejected and H_1 accepted.

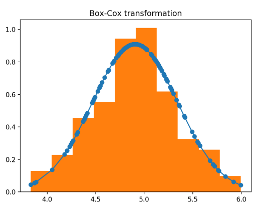
Sample 6: All, total time on task 2
P-value: $2.57 * 10^{-9}$
The p-value is lower than the significance level (0.05), the null hypothesis is rejected and H_1 accepted.

Sample 7: All, total time on task 3
P-value: $1.71 * 10^{-11}$
The p-value is lower than the significance level (0.05), the null hypothesis is rejected and H_1 accepted.

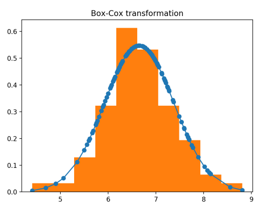
The samples was then Box-Cox transformed. The histograms after the transformation is shown in figure 4.9a, 4.9b and 4.9c. A visual analysis says that these histograms looks approximately normally distributed.



(a) Sample 5 - Task 1



(b) Sample 6 - task 2



(c) Sample 7 - task 3

Figure 4.9: Histogram with normal distribution fit after Box-Cox transformation, sample with total time per task

The D'Agostino and Pearson normality test confirms the visual conclusion. The data is normally distributed after the Box-Cox transformation.

D'Agostino and Pearson normality test
(After Box-Cox transformation)
Significance level: 5%

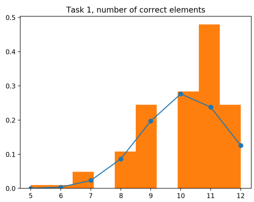
Sample 5: All, total time on task 1
P-value: 0.164
The p-value is higher than the significance level (0.05), the null hypothesis is accepted.

Sample 6: All, total time on task 2
P-value: 0.982
The p-value is higher than the significance level (0.05), the null hypothesis is accepted.

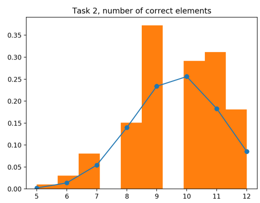
Sample 7: All, total time on task 3
P-value: 0.354
The p-value is higher than the significance level (0.05), the null hypothesis is accepted.

Sample 5, 6 and 7 is normally distributed and to analyse these samples one can use parametric methods.

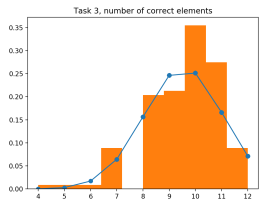
4.3.2.4 All participants - Task 1, Task 2 and Task 3 - correct elements per task



(a) Sample 8 -Task 1



(b) Sample 9 - task 2



(c) Sample 10 - task 3

Figure 4.10: Histogram with normal distribution fit, sample with correct elements per task

D'Agostino and Pearson normality test
Significance level: 5%

Sample 8: All, correct elements in task 1
P-value: 0.00022
The p-value is lower than the significance level (0.05), the null hypothesis is rejected and H_1 accepted.

Sample 9: All, correct elements in task 2
P-value: 0.099
The p-value is higher than the significance level (0.05), the null hypothesis is accepted.

Sample 10: All, correct elements in task 3
P-value: 0.0047
The p-value is lower than the significance level (0.05), the null hypothesis is rejected and H_1 accepted.

5 | Proposed sections

5.1 Future work

Create a survey to test how accurate both experienced and inexperienced participants digitize buildings from aerial images. Can use FKB as the correct polygon and compare it with the drawn polygon from participants.

Do a study with reward. Compare reward and not reward geo tasks. Do they solve the tasks better with reward? "A reward can be provided for merely participating in the task. The reward can also be provided as a prize for submitting the best solution or one of the best solutions. Thus, the reward can provide an incentive for members of the community to complete the task as well as to ensure the quality of the submissions."

The future in micro-tasking "belongs to hybrid methodologies that combine human computation with advanced computing" (Meier, 2013b).

When aiming towards wider adoption of crowdsourcing one have to be aware of the challenges of using it. It is important to remember that all tasks do not fit into the micro-tasking crowd worker model. Very complex tasks that can't be partitioned are not suitable for solving through micro-tasks.

Advanced computing techniques such as Artificial Intelligence and Machine Learning is needed to build approaches that combine the power of people with the speed and scalability of automated algorithms (Meier, 2013b).

5.2 Usage potential

A machine learning company called "developmentSEED" use a micro-tasking solution for cleaning machine learning output data. They have created a GUI web application solution called Skynet Scrubber. In their blog, Derek Lieu writes: "Skynet gets more capable every day, but the output is still not perfect [..] We built Skynet Scrub so we could start using Skynet data sooner".

Systems are exploiting the people's physical presence in an environment more, they are more location dependent. This can be particularly important when seeking to improve geospatial data quality [(Meier, 2013b), p. 323]. "For instance, UrbanMatch (Celino et al. 2012a) is a mobile location based game that uses player's familiarity with a city to link photos with points of interest in the city. Players are shown points of interest and known images from a trusted source (e.g. OpenStreetMap) and asked if photos from an untrusted source (e.g. Flickr) might also relate to the point of interest ".

(Meier, 2013b): "As the previous sections show there is a lot of potential for AR systems to use HC to provide content, and to support processing in other ways. However there has been little research to date combining AR and HC systems. In this section we review the first research efforts in this area. "

(Meier, 2013b) "Lastly, there is huge untapped potential in leveraging the “cognitive surplus” available in massively multiplayer online games to process humanitarian microtasks during disasters. The online game “League of Legends,” for example, has 32 million players every month and three million on any given day. Over 1 billion hours are spent playing League of Legends every month. Riot Games, the company behind League of Legends is even paying salaries to select League of Legend players. Now imagine if users of the game were given the option of completing microtasks in order to acquire additional virtual currency, which can buy better weapons, armor, etc. Imagine further if users were required to complete a microtask in order to pass to the next level of the game. Hundreds of millions of humanitarian microtasks could be embedded in massively multiplayer online games and instantaneously completed. Maybe the day will come when kids whose parents tell them to get off their computer game and do their homework will turn around and say: “Not now, Dad! I'm microtasking crisis information to help save lives in Haiti!” "

Machines are bad at tackling things they have never seen before. They need to learn from large amounts of passed data. Humans don't need this. Humans can solve tasks we have never seen before. Tackling new/novel situations are humans much better than machines. Business strategies, marketing holes, this are tasks only humans can do.

Data Categorization, organize your data, no matter what the data is. Micro-tasking platforms can turn all the big data into rich data that is organized, streamlined, and useful. Micro-tasking let's you organize your original data which again can be used to train machine learning models. According to CrowdFlower is human-curated training sets the best traning datasets to use.

Appendices

A Tets

Fbox

Some text esfljsf lskj lksdjflsk slk

Some text kduhaszkdh aszkdjhs zkjdfh skdj skd

dwkjdkwjdh wkjdhw kjdh wkjhd qwkjhd kwd qw .

text

dwkjdkwjdh wkjdhw kjdh wkjhd qwkjhd kwd qw .

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