# Using Open Street Map for Content Creation in Location-Based Games

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*Abstract*—**Location-based games have been around since 2000. In these games, players are required to move and interact with objects in the physical world. Players need to reach a set of targets by moving outdoors. The targets are real objects (amenities) like statues, restaurants, bridges and contain the name, location, and a representative image. The main challenge is finding content and creating games where there is playing interest. In this paper, we study the use of OpenStreetMap (OSM) for content creation. We study the availability of amenities in different regions and whether they contain sufficient metadata for generating targets. We found that even if the data within OSM itself lacks images; many amenities refer to external links like Wikipedia pages and individual websites, from which we can extract the desired content about 21% of the time. This approach outperforms previously studied methods including Web crawling, geotagged photo datasets, and photo-sharing services such as Flickr. However, OSM data is greatly underrepresented in Asian countries and good results are limited to urban and downtown areas.**

## I. Introduction

During the last decade, accurate positioning receivers were added to smartphones, making them easily available to the masses. This technology allows people to not only actively participate in the collection, editing, and usage of geodata such as photos, notes, videos, and trajectories but also made it possible to develop location-based games (LBG's). The global success of popular location-based games Ingress and Pokémon Go have shown significant public interest in this domain. Studies indicate that playing LBG's have positive health influences also [1].

One problematic factor for these games is content creation. The reason is that it requires visiting outdoors, collecting game content, and attaching digital content to real-world locations, which is a very challenging task [2]. Even simple treasure hunt-type games require a huge number of locations everywhere in the world. Pokémon GO and Ingress share a community-built database of locations spread worldwide. However, users still complain about the lack of locations in many places. That is why LBG's are often difficult to survive over time [3]. In general, the game content creation process is crucial to a game's success.

Having not enough or poorly done content could provide an unsatisfactory gaming experience [4]. While action, fantasy, and role-playing games are more popular, simple treasure hunt games are still one of the main genres in location-based games. These games merely focus on visiting pre-defined locations and interact with whatever is found at the location. A classic example is *Geocaching*. Other games may also add questions or tasks like photo taking at the target location. Nevertheless, they all share the same bottleneck: how to create content to be played everywhere in the world.

O-Mopsi is an example of a treasure hunt game. It is an orienteering game [5] played in an outdoor environment. It was first released in 2010 during Scifest, the Annual Science festival in Joensuu, Finland [6]. The goal is to find real-world targets using smartphone with GPS-guided navigation. To complete a game, a player needs to walk from 1km up to several kilometers, depending on the length of the game. Besides, the physical movement, O-Mopsi serves sight-seeing and educational purposes. Currently, the games created in O-Mopsi are mostly inside Finland and few others elsewhere. The content is manually created by game administrators and players. However, a small database of photos from the View on Cities website is also being used. The issue is that people elsewhere who have downloaded O-Mopsi do not find games in their regions to play [5].

Various approaches have been studied to automate the process of content creation such as a web crawler [7], photo-sharing service APIs (Flickr, Smugmug, Pixabay), and geotagged photo datasets (YFCC100M) [8]. However, the need to have useful content all over the world is not satisfied. There are huge challenges with issues like API restrictions, poor image quality, and content, missing textual annotations, insufficient content in the specified region, and positional accuracy have remained a concern.

In this paper, we explore OpenStreetMap (OSM) data to be used as content in O-Mopsi. Its main benefit is that it provides free geographical data to anyone who wants it, without any legal or technical restrictions [9]. It also owns a high user base, which ensures continuous data update and completeness. We mine OSM data to collect points of interest (POI's), their short textual description, and a representative image, which the OSM database does not store itself. However, the amenities representing POI's often refer to external links like websites and Wikipedia pages, which may contain useful images, if extracted.

The rest of the paper is organized as follows. Section II discusses the potential content sources. Section III presents OSM as a content creation source. Experimental results, OSM data and limitation, and Conclusions are discussed in Sections IV, V, and VI respectively.

## II. Potential Content Sources

O-Mopsi [10] is a location-based game developed by the machine learning group at the University of Eastern Finland [5]. The objective is to find a set of real-world targets using a smartphone with GPS-guided navigation. To complete a game, the player needs to visit all the targets, as quickly as possible by moving outdoors. The pictures of the targets are shown on the map. A player can choose free order to visit the targets (see Fig. 1). Reaching a target is automatically detected using GPS. However, a target is successfully reached when the distance becomes less than 20 meters.


Fig. 1. O-Mopsi game overview

Each target is a real item such as a statue, restaurant, bridge and contains its name, location (coordinates), and a representative image of the target as shown in Fig. 2.


Fig. 2. O-Mopsi target elements

Besides the accuracy of a target's location, the quality and content of its representative image also hold a big concern. Images are an important clue for the players to find the targets. Images themselves are easy to produce but there exist many design pitfalls that only an experienced content creator can avoid. Anyone can take pictures, but only a few take aesthetically good pictures. However, while using images from sources that are dedicated to other purposes, image content and quality can pose more serious challenges.

Images depicting clearly recognizable objects serve as a good target (see Fig. 3). However, images taken from a far distance, containing multiple objects and likely to disappear very fast should not be considered (see Fig. 4). Good design principles can be found in more detail in [11].

The biggest challenge we have is having not enough content around the world. People who have downloaded O-Mopsi do not find games in their area to play. Currently, we have used crowdsourced pictures from the Mopsi database and downloaded a small database from the View on Cities website, which mostly covers selected areas in Finland and few other European countries.


Fig. 3. Desired images


Fig.4. Undesired images

To obtain a big number of geotagged images worldwide, we have studied different approaches such as Web crawling, social media APIs, and geotagged image datasets. The proposed Web crawler [7] found only <1% of the images having geo-tag embedded in its Exif metadata. To improve the number of geotagged images further, geoparsing tools were used which improved the results to 5%, which is still very modest.

Possible reasons for insufficient results were addressed due to exclusion of geolocation and other EXIF data because of the following reasons:

- Size limitations of the websites.
- Privacy concerns.
- Web site performance optimization.

During the crawling process, the seed website plays an important role. Websites about travel and photo sharing services serve as a good source for geotagged images compared to the websites about business and blogs [7].

Geotagged image dataset known as YFCC100M dataset [12], comprising of 40 million geotagged images collected worldwide, was explored. However, it concerns issues like the aging of the dataset, quality of the image and content, accuracy of coordinates, and insufficient content in desired gaming region.

Social media services such as Flickr, SmugMug, and Pixabay also provide geo-location with images. However, these images are contributed mainly for photography reasons. Thus, the suitability of the content is a big issue and needs automatic filtering or peer review, to choose the images that fit O-Mopsi definition for a representative image. The location where the image was taken and the actual location of the object also requires careful consideration [13]. API restrictions for the limited number of images is another bottleneck.

## III. Utilizing OSM as Content Source

In this article, we target OpenStreetMap (OSM) database with the intention of content creation purpose. In a little over a decade, OSM has become a famous example of user-generated content (UGC), with millions of users. The easy access and continuous update of the OSM database have allowed a large number of industry actors, developers, and humanitarian operators to use OSM data for a variety of purposes. The rich and heterogeneous nature of data has further led to the creation of new tools in the sphere of disaster prevention, education, welfare, routing, tourism, energy, topography, and algorithmic model development. Games like Collapse – The Division Game, OSM game Kort and StreetComplete have also benefited from OSM data [8],[14].

Siriaraya et al. [15] used OSM data and GSV (Google Street View) to propose a context-aware storyteller system that tells the stories to the users based on the context of their location. We mine OSM data to collect targets for O-Mopsi using the strategy shown in Fig. 5.

The method uses a bounding box as an input. In the first step, OSM amenities are queried in the desired region using the following Overpass API query at OSM web-based data mining tool [16].

```
[out:json][timeout:25];
(
node[amenity=](if:is_tag(website))({{bbox}});
);
out body;
```

For these amenities, OSM contains the title and the location which are both needed by O-Mopsi. The one thing that is missing is an image. OSM itself does not store any images. However, some amenities contain a link to a webpage which may contain images if inspected. We, therefore, consider amenities that have a webpage link as target candidates and discard amenities that do not contain a webpage link. All resulting amenities are considered as candidates.

In the next step, we extract a representative image from the website (see Fig. 6). If the website is a Wikipedia page or some other service with systematic formatting, it is easy to implement automatic extraction by parsing the document object model (DOM) of the webpage and selecting the tag containing the image. Some services, like Wikipedia, even offer APIs for doing this.

If the web link points to a personal webpage, the process is usually more difficult. Automatic image extraction methods exist [17], but the quality of the output varies significantly and in the case of O-Mopsi, the quality of the image is important. For example, both images in Fig. 6. are from the same website and represent the location *Taitokortteli*. However, only the image on the left is taken outside and is useful as an O-Mopsi target. Doing such a decision automatically is not trivial. Therefore, we perform a manual inspection at this stage. If the main page does not contain any images, a short crawling process is applied with the main webpage as the starting seed [7].

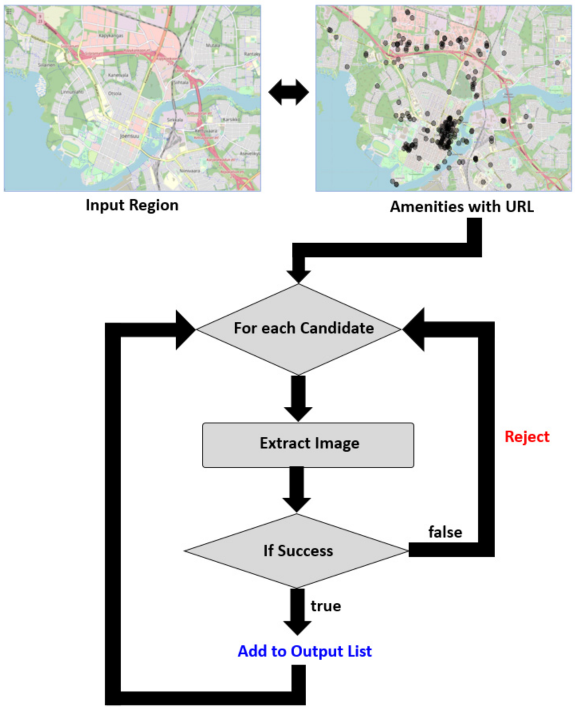


Fig. 5. O-Mopsi content creation from OSM


Fig. 6. A location Taitokortteli image and two representative images extracted from the web page

## IV. Experimental Results

We perform an analysis to estimate how many amenity web links have representative images which we can use for the game. To assess the quality of the data contained in amenity web links, we loaded images using a custom-built tool that allowed reviewers to mark down which images are representatives if any. We did this investigation only in the city of Joensuu, Finland as it is quite time-consuming and because those who use this tool need to be familiar with the city and its amenities. Two reviewers who reside in Joensuu volunteered for this purpose.

Table I shows the overall summary of the data collected. From the total of 330 web links provided by OSM, 310 are still working, so, one concern comes from the update frequency of OSM data itself. However, this seems to be a minor issue and the data in Joensuu is mostly up to date. From the working web links, 67.3% have images that can be considered representative.

TABLE I. OVERALL SUMMARY OF COLLECTED DATA

| | |
|---|---|
| Websites | 330 |
| Working websites | 310 |
| Websites with representative images | 198 (67.3%) |
| Websites with target images | 62 (21.1%) |
| Representative images per website | 6.3 |

To conclude this number all images were first downloaded and associated with the name of the service. Then, two human observers reviewed all downloaded images and whenever there was a difference of opinion on what constitutes a representative image or not, they reached a common decision. Note that some of the websites showed additional images which were useful, however, they could not be downloaded for different reasons such as images that are not part of the DOM itself, but are loaded dynamically afterward, perhaps even after some user interaction. We did not include these in our statistics.

On average, there are 6.3 good images per website. In 21.1% of the time, an image of the actual location (building or object) is present. This is ideal in the case of O-Mopsi. However, the other ones can be used as well in most cases to give a general idea to the player of what kind of place he/she is looking for (see Fig. 6). This labeled dataset can be inspected and downloaded [18]. We did a quick inspection in other cities as well and we consider these numbers to be representative in general, not only in the city of Joensuu. Based on this small pilot we report that 67.3% of the amenity websites contain a representative image. We can confirm this only for the city of Joensuu at the moment but we expect this to generalize to other cities in Finland, and a certain extent to other cities of similar size in Europe. Most amenity websites seem to include a useful representative image.

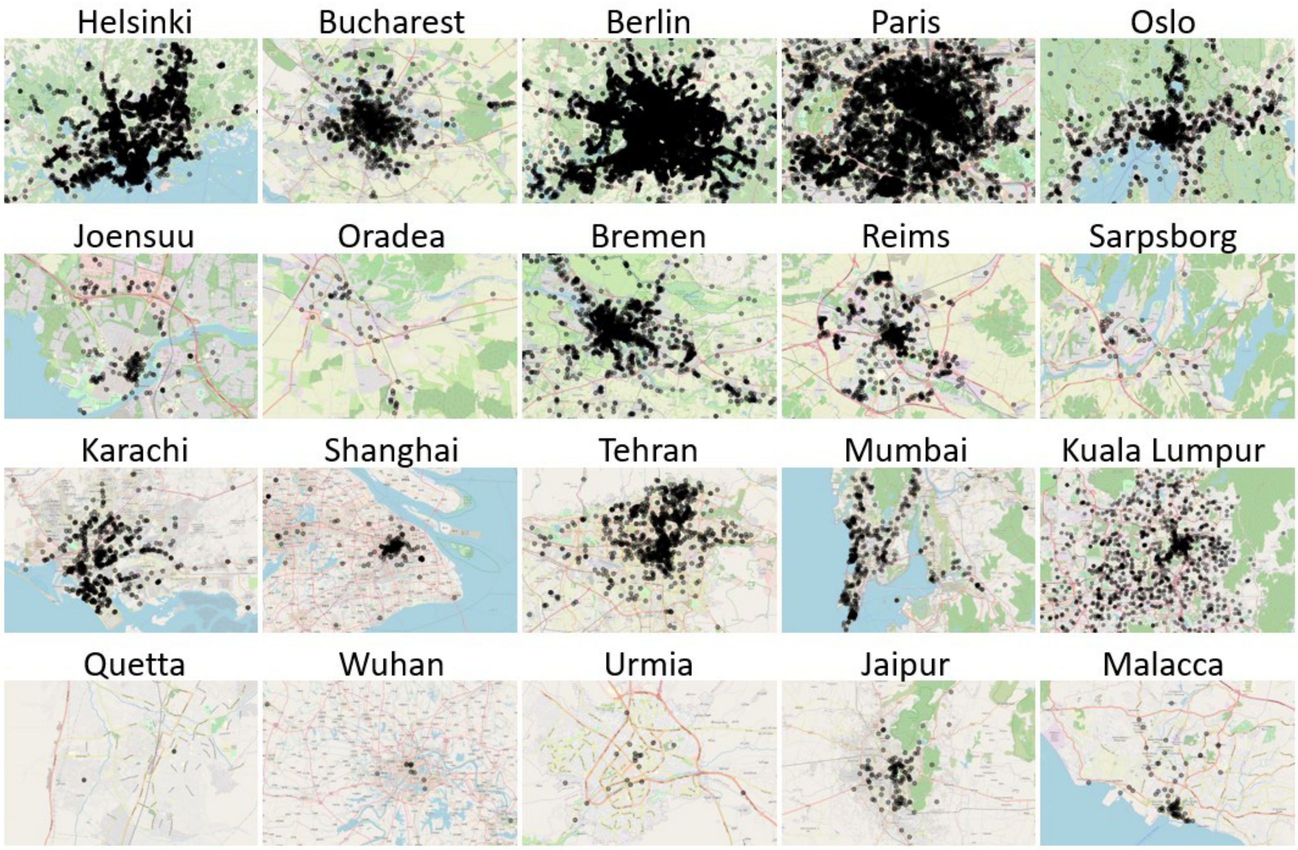


Fig. 7. Amenities with websites extracted from different regions in Europe and Asia

TABLE II. OSM AMENITIES IN EUROPE AND ASIA

| Europe | | | | | | |
|---|---|---|---|---|---|---|
| Country | Large/Small City | Population | Amenities | Amenities per 100,000 people | Websites | Wikipedia |
| Finland | Helsinki<br>Joensuu | 1,520,058<br>76,543 | 7843<br>330 | 516<br>431 | 7897<br>330 | 475<br>3 |
| Romania | Bucharest<br>Ordea | 1,883,425<br>196,367 | 1130<br>56 | 60<br>29 | 1148<br>56 | 89<br>1 |
| Germany | Berlin<br>Bremen | 3,769,495<br>567,559 | 18863<br>2162 | 500<br>381 | 18863<br>2162 | 192<br>121 |
| France | Paris<br>Reims | 10,784,830<br>182,460 | 8265<br>777 | 77<br>426 | 8265<br>777 | 280<br>5 |
| Norway | Oslo<br>Sarpsborg | 1,019,513<br>56,559 | 1931<br>54 | 189<br>95 | 1931<br>55 | 34<br>0 |
| **Average** | | 20,056,809 | 41411 | 2704 | 41484 | 1200 |

| Asia | | | | | | |
|---|---|---|---|---|---|---|
| Country | Large/Small City | Population | Amenities | Amenities per 100,000 people | Websites | Wikipedia |
| Pakistan | Karachi<br>Quetta | 14,910,352<br>1,001,205 | 680<br>2 | 5<br>0,2 | 681<br>2 | 25<br>1 |
| China | Shanghai<br>Wuhan | 24,281,400<br>8,896,900 | 321<br>12 | 1<br>0,1 | 321<br>12 | 8<br>1 |
| Iran | Tehran<br>Urmia | 9,033,000<br>736,224 | 1018<br>19 | 11<br>3 | 1018<br>19 | 4<br>1 |
| India | Mumbai<br>Jaipur | 12,478,447<br>3,046,189 | 490<br>127 | 4<br>4 | 492<br>129 | 153<br>5 |
| Malaysia | Kuala Lumpur<br>Malacca | 1,588,750<br>484,885 | 1401<br>80 | 88<br>16 | 1401<br>80 | 19<br>36 |
| **Average** | | 76,457,352 | 4150 | 133.33 | 4155 | 253 |

Next, we analyze the distribution of the OSM data in different parts of the world. We extracted amenities in two cities (the 1st and 10th largest) of ten different countries from Europe and Asia as shown in Fig. 7. It is important to note here that, we are dealing with estimations using Bbox for chosen cities. A summary of statistics for each city is given in Table II.

We report that the number of amenities is about 20 times greater in the larger cities, except the cities of Karachi and Quetta, where Quetta has an almost negligible number of amenities. However, the population is 22 times greater in larger cities than the smaller ones in Europe and 8 times in Asia.

The amenities and population size correlate. In Europe, there are roughly 206 amenities per 100,000 people. In Asia, there are only 5. This means that the amenity database is greatly under-represented in Asia with 14 times more data in Europe than in Asia. Berlin and Kaula Lumpur has reportedly the highest number of amenities, respectively, which shows the high user base of OSM data in these regions.

Table III shows the list of the top 10 cities with the most amenities and most amenities per 100,000 people, sorted in descending order. Helsinki has reportedly the highest and Bucharest has the lowest number of amenities per 100,000 people. Correspondingly, Berlin has the highest and Karachi has the lowest number of amenities.

TABLE III. TOP 10 CITIES BASED ON MOST AMENITIES AND MOST AMENITIES PER 100,000 PEOPLE

| **Amenities** | | **Amenities per 100,000 people** | |
|---|---|---|---|
| Berlin | 18863 | Helsinki | 516 |
| Paris | 8265 | Berlin | 500 |
| Helsinki | 7843 | Joensuu | 431 |
| Bremen | 2162 | Reims | 426 |
| Oslo | 1931 | Bremen | 321 |
| Kuala Lumpur | 1401 | Oslo | 189 |
| Bucharest | 1130 | Sarpsborg | 95 |
| Tehran | 1018 | Kuala Lumpur | 88 |
| Reims | 777 | Paris | 77 |
| Karachi | 680 | Bucharest | 60 |

We next inspect the content density of 6 different O-Mopsi games (see Fig. 9), created by game administrators with the content generated from OSM and a popular photo-sharing website Flickr. The images collected from Flickr include only public images. Thus, we exclude private and semi-private photos from our experiment. Our intention here is to find out if we can get enough targets from OSM and

Flickr in specified game regions, to automate the O-Mopsi content creation process.

The length of the selected games is between 2-3 kilometers and the number of targets varies from 10-15. We suggest the number of targets between 3-5 per kilometer, to keep the players motivated and focused. Having targets dispersed over longer distances can cause boredom and eventually lose the player's interest. The collected images were then analyzed by a human observer to estimate how many of them can be used as O-Mopsi targets. The ratio of useful images found was not very encouraging except for one gaming region (Kuopio). For games named Jokiasema and Kontiolahti, both OSM and Flickr did not return any targets (see Table IV). Despite having a large number of images from Flickr in Jokiasema, none could serve as a target, and needed to be discarded (see Fig. 8).

Reasons for discarded images are as follows:

- Images depicting the purpose of service only (Representative images).
- Images of people, food, and animals which are not likely there anymore;
- Images having a nice object to serve as a target, but includes additional objects, which can make player confuse about the actual object to reach;


Fig. 8. Examples of discarded images

In the case of Marjala (suburban of Joensuu), there are 3 amenities in OSM but none of them is suitable, while 1 target is found from Flickr. Similar results are obtained in Pentillä, despite that, it is close to downtown. This time 7 amenities appeared in OSM, resulting in 1 target, while none in Flickr. The game Scifest 2016 in the UEF campus area, got 3 targets from Flickr but not quite enough to make a reasonable game (see Fig. 10). Better results are obtained in city downtowns. For example, in Kuopio downtown, we found 17 targets from OSM and 6 from Flickr (see Fig. 11). These numbers are already sufficient for the automated content creation process of the O-Mopsi game.

We conclude that fewer images from OSM are due to the fact that a small number of amenities were found in most gaming regions. For Kuopio large number of amenities found, lead to good results. We can further say that OSM performed well in downtown areas but does not provide sufficient data in suburban and rural areas. Flickr returns far more images than OSM, but most of the images were about people, animals, and other objects that are not permanent landmark or building and therefore not likely to be there later; hence they were discarded. Regions, where Flickr does not return targets, is also because people did not find enough attractions or because of the lack of photographer's interest. Such areas can be suburban for example, and they should still be suitable for playing.

TABLE IV. O-MOPSI GAMES CONTENT FOUND FROM OSM AND FLICKR

| | | Games | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | **Jokiasema** | **Marjala** | **Penttilä** | **Kuopio** | **Kontiolahti** | **Scifest 2016** | **Average** |
| **O-Mopsi** | Targets | 14 | 11 | 10 | 9 | 8 | 13 | 65 |
| **OSM** | Amenities found | 6 | 3 | 7 | 28 | 3 | 7 | 54 |
| | Website links | 6 | 0 | 7 | 35 | 4 | 7 | 59 |
| | Targets found | 0 | 0 | 1 | 17 | 0 | 0 | 18 |
| **Flickr** | Total images | 249 | 8 | 99 | 811 | 3 | 53 | 1223 |
| | Targets found | 0 | 1 | 0 | 6 | 0 | 3 | 11 |


Fig. 9. O-Mopsi games chosen for experimental purpose

## V. OSM DATA LIMITATIONS AND CONCERNS

In OSM, amenities are usually represented as points, especially when the target is small or a part of a large building. Sometimes, however, amenities appear as polygons when they represent entire buildings. These polygons can be reduced to single points if needed, by calculating the geometrical center of mass. In the case of O-Mopsi, we select a location on the side of the building so that players do not need to enter a potentially closed building where GPS location also does not work.

## VI. CONCLUSION

We studied the potential of OSM data to act as a geo-tagged image collection source with the intention of content creation for O-Mopsi. We collected the OSM amenities containing web links, in the region of Joensuu using Overpass API. Representative images were collected from websites using a tool custom-built for this purpose.

Our results showed that the ratio of images at location (an ideal case for O-Mopsi) is considerably low as compared to the representative images 21.1% and 67.3% respectively. However, finding images at the location required manual inspection and local knowledge. Though, representative images can be used to find what kind of services are located in a particular region. However, the quality of images collected, and positional accuracy needs consideration before use.

Studying the distribution of OSM data in different parts of the world, by choosing big and small cities of 10 different countries in Europe and Asia, showed that the number of amenities and population size correlates. Europe has 14 times more data than Asia, which means OSM data is underrepresented in Asia. The content density of O-Mopsi games, collected by the game administrators was next compared with the content collected from OSM and Flickr. Results showed that OSM has a high potential to provide enough targets in downtown and urban areas. However, automatic filtering of non-useful content and scarce data in rural and suburban areas still needs consideration. In comparison to Flickr, OSM found more targets in downtowns but in rural areas, Flickr and OSM both have limited or no targets at all. Flickr had further returned far more images than OSM, regardless of the region, but most of them were not useful, hence were discarded. However, in downtown areas, Flickr's probability of finding targets is high also. We conclude that Flickr images are dependent on the photographer's interest, thus results could be highly unpredictable.

A limitation of using OSM is that it is only semiautomatic as it stills requires human inspection. As a future work, we aim to extend the research by providing the fully automated system to replace manual inspection of the images.


Fig. 10. Content generated for games Marjala, "Penttilä" and SciFest 2016 from game administrators, OSM and Flickr

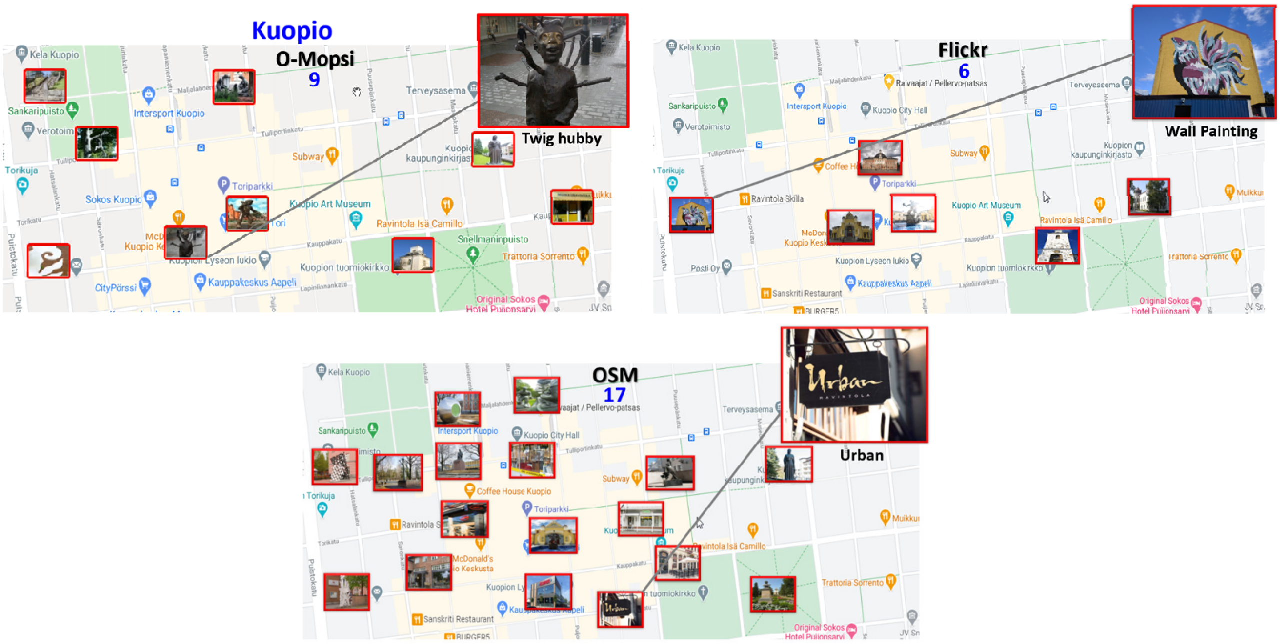


Fig. 11. Content generated for game "Kuopio" by game administrators, Flickr, and OSM respectively

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