TECHNISCHE UNIVERSITÄT DRESDEN

Faculty of Environmental Sciences Institute for Cartography

Master Thesis

Comparison of manual and automatic tags for mapping of human activity

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Born on 09.04.1990 in Alexandria, Egypt

Submitted for the academic degree of

Master of Science (M.Sc.)

Date of Submission 15.10.2018

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Statement of Authorship

Herewith I declare that I am the sole author of the thesis named

„Comparison of manual and automatic tags for mapping of human activity“

Which has been submitted to the study commission of geosciences today.

I have fully referenced the ideas and work of others, whether published or unpublished. Literal or analogous citations are clearly marked as such.

Dresden, 15.10.2018 Signature

Acknowledgement

الحمد لله رب العالمين.

All praise be to Allah the merciful and the kind.

I am grateful to everyone that helped me through this journey. First of all, special thanks to my supervisor *Prof. Dirk Burghart* for his extreme patience, guidance and understanding.

I would like also to thank my dad, I am blessed to have you in my life. Special appreciation to my girlfriend *Kate Doyle* for her motivation and support all the way. Sincere thanks to my brothers *(Beltagy, Salama & Habashy)* you guys supported me in many ways.

Finally, I dedicate this work to my mother *Salwa El Masry*.

Abstract

People have high appreciation of moments and love to take pictures to represent these moments. This trend is increased dramatically as almost every one owns a cell phone featuring camera. With social media rising popularity, these moments are now shared with family, friends and even unknown followers. This caused an explosion of online media content and images to become one of the most important data representation for human activity.

As these online media content increase drastically, means of organizing such resources emerged via annotating “Tagging”. As manual tagging is subjective (dependent on annotator) and time demanding, automation of this step is very useful and further advancement in this particular area are being achieved. This study aims to compare the outputs of both systems “Manual and automatic tagging” for the representation of human activity to draw a conclusion regarding how close these representation are.

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List of abbreviations

CBIR: Content based Image retrieval

IR: Information retrieval.

ESP: Extrasensory perception

API: Application program interface

SQL: Structured Query Language

TXT: Tab separated file.

CSV: Comma separated file

AOI: Area of interest.

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Chapter 1: Introduction

This chapter is an introduction to the thesis research, it discusses the motivation and problem statement behind the study. Also it provides an outline for thesis structure and organization. This aim to familiarize the reader with study general ideas and concepts.

1.1 Background

Human activity always attracted considerable amount of research interest in the field of geography, while this is true, the usage of images or photographs in the analysis of human activity related to time and space is quite a new field (Kwan, 2004).

In the pre-digital era, image production was mostly handled by professional photographers and specialized personal, also access to image capturing devices was restricted to certain individuals, as these devices were quite expensive and careful handling was required. As for presentation and sharing of the captured moments and scenes, physical image had to be developed for representation of these events

As smartphones popularity rose, owning an image capturing hardware became very common, as cameras became integrated into every smartphone (Gantz, 2008). This and in addition to the rise of social media, there became an explosion of multimedia content available online (Wang, et al., 2010). Examples of such social media platforms are image sharing websites such as Flickr[1] and Instagram[2] which became and continued to become tremendously popular; for example Flickr is currently hosting over 7 billion images since it is launch(Flickr[1]) and there is more than 20 million photos uploaded Instagram per day(Instagram[2]). Due to such rich media content availability; handling and understanding of this digital information became very vital, this resulted in a growth of research work concerned with such fields and its related topics, and this increase interest was predicted long before this situation and this attraction trend continues to grow over time as more and more information are becoming available (Datta, 2008).

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

[2] https://www.instagram.com/

Such media content richness demanded creation of libraries or search words that allow for easier and faster retrieval of such resources. Social media platforms allow the user to annotate the uploaded content with descriptive key words named tags. Tags are considered metadata allowing for a convenient search and retrieval of shared images or resources.

1.2 Problem statement

Prior to the rise of social media, annotation processes were desktop based (e.g. Adobe Photoshop album), this process had its benefits of organizing personal photo libraries, but despite this, it was mainly avoided and users did not bother to tag their images (Rodden & Wood, 2003.). These processes required spending effort and time in annotating the images, whilst the benefits of carrying out this process were neither very clear nor rewarding (Ames & Mor, 2007). On the other hand, in image sharing platforms the benefits are quite clear for image annotating (tagging). The tag acts as an image keyword, allowing discovery and retrieval of image via searching. This allows images to be accessible to any member of the online community, providing a greater reach and exposure.

As a highlight to the importance of the tagging process, commercial companies and newspapers employ teams for image viewing and tag words assignment, the teams annotate the image with the best represented words, and this is considered as an indexing process allowing for faster future retrieval of the resource. These tags are generated and assigned manually by dedicated teams of personal (Markkula & Sormunen, 2000).

Considering humans are involved with tag assignment, manual image tagging is often subjective as every individual conceptualize the image in different ways. This results in different image perception causing similar images to be perceived and tagged differently by different people (Sen, et al., 2007). These differences occur due to many aspects such as (culture, language, mood etc.). While, humans respond to visual elements of the image (color, texture, spatial distribution, blobs etc.), this is overpowered by the cognitive reasoning of semantic content (Greisdorf & O'Connor, 2002) , and this reasoning will differ from one person to another. A study was performed on Flickr platform concluded only around 50% of user tags were image related (Kennedy, et al., 2006).

With such problems accompanying manual tagging, as well as the drastic increase in digital data volumes, popularity among the IR (Information retrieval) and CBIR (content based information retrieval) is rising. The general idea of the automatic tagging systems is generates relatable tags automatically according to image contents, these tags should accurately describe the image major aspects and represent its content truly (Enser PG, 2005).

Proper evaluation of this automatically generated tags especially concerning human life and every day activities is important, as social media with its image and moments sharing features are becoming a very important everyday trend and behavior representative. In addition its evolution to be one of the main source of information and updates as every day activities such as breakfast, dinner, parties is represented as an image and shared on some form of social platform.

Assessing how people represent their activity in form of image tags with a computerized analyzing system “ tag generating " system will guide to faster analysis and understanding of human behavior.

1.3 Research objectives

The overall goal of master thesis is using one of the available automatic tag generating systems and performing a comparison of results with the manually assigned tags for the same image resources. Image data resources are collected from Flickr platform for Dresden area. Processing and data extraction is crucial as the study will address the areas of (Alaunpark & Großergarten). In order to reach the study´s objective, the following research questions will be addressed.

- Which tag generating system is best suited for our study?
- How to implement such system?
- Which comparison and evaluation method will be adopted by the study?
- How the result will be properly visualized?

1.4 Thesis outline

Chapter1: Introduction and research objective and scope description.

Chapter2: Literature review.

Chapter3: Methodology and workflow.

Chapter4: Results.

Chapter5: Discussion.

Chapter6: Conclusion.

Chapter 2: Literature review

This chapter presents and discuss some of theoretical background information and related work. Basic definition and explanation of research terms such as tags and tagging systems is presented, explanation of evaluation and comparison methods is also described.

2.1 Theoretical background:

2.1.1 Tagging

Since 1999 effective labeling of photos is an active field of research and has been addressed in variety of research works (Ames & Naaman, 2007). **Tagging** is defined as the web resources labelling according to its content (webpage, image, blog) and the tag should represent a topic inside the resource (Medelyan, et al., 2009) (Lancaster, 1991). **Tags** are words describing image context and in order to explain tags we should first explain context. *"**Context**: Any information could be used for situational description of an entity. Possibilities of entity are person, place or an object that is relevantly considered for the interaction between user and application, this includes the user and application themselves"* (DEY, 2001) *.* Usable information are only regarded as context, and the usage of the most relevant information is key for an accurate description of the entity. In this study, the entity is the image.

Tags are usually associated with resources such as webpages or photos created by the user, they are exhibited as a form of free chosen keywords not bonded to certain vocabulary or structure. This result in unstructured knowledge as tags do not contain an explanation for prior semantics[3]. Although tag have unstructured nature, this particular property is its main benefit (Rattenbury, et al., 2007).

Tagging depended upon for its structure on the emerging social behaviors and trends for its user community, as well as for its linguistical structure. The user community

[3] Branch of linguistics and logic concerned with meaning.

overtime developed a unique structure for resource definition. This observation caused the defining of the popular tag words as *folksonomy* (Noruzi, 2006) .

Tags are image annotation that purvey contextual information of the image (Ames & Naaman, 2007). As the number of photos increase to thousands, Image annotation proves to be of useful benefits; it assist in image search and recall. Claims has been made that tagging would overtake classification as an organizational method due to its extreme popularity (Voss, 2007).

2.1.2 Manual tagging

As beneficial as image tagging seems, manual image tagging was often avoided in personal usage, as the benefits of this method were vaguely understood and did not compensate the time and effort spent, the process was only desktop based and its benefits was strictly personal (Kirk, et al., 2006).

As social media became popular, a break out of multimedia content has been witnessed (ex. Flickr, Instagram etc.) (Liu, et al., 2009). Member contributed data of these sources has been used widely examined for studying human and social behavior (Sakaki, et al., 2010).Taking a look at Flickr as study case, it is now hosts more than 7 billion images (Flickr, 2018) and with such increase in content; accurate and fast retrieval methods must be implemented for a better organization of such huge contents. Flickr allows the annotation of these shared content as tags added by the uploader, (Marlow, et al., 2006). Benefits of tagging to the user became very clear, as tagging allows for the images uploaded to be searchable, therefore accessible to any member of the online community, allowing for great exposure and reach (Ames & Mor, 2007). Also in addition, contributing and sharing of general ideas and information regarding some places and events to either informed or uninformed interested audience. Furthermore some users seek attracting attentions as he might share the image and choose a popular word in the tag cloud as the tagging word. The tag cloud is considered the common popular tags, therefore the shared resources becomes even easier to find. Some users also tag for the idea of self and opinion-expression , one might annotate an image with tag words like “elitist, free thinker” expressing his mentality and opinion (Marlow, et al., 2006).

Consideration of manual annotation problems is important, adding to the challenges mentioned in the introduction section, users often apply multiple tags having same meaning and just spanning over the semantic space for tagging an image, such tags are considered noise (Kennedy, et al., 2006) , Example such as usage if tags “fun, relax, chill, peaceful” they all represent the idea of relaxation and they are different yet the same. Also, image annotator tend to ignore the obvious visual aspects of the image and address the very difficult conceived image perspectives (Barnard, et al., 2003). Determining tag quality is always a challenge as one study concluded that only 21% an online community tags was worthy of display, some tags maybe misleading offensive or inappropriate as there is lack of control over the assigned and displayed tags (Sen, et al., 2007). In addition tags serves as a link to other different resources having the same tag or keyword which confirms the mentioned benefit of discovery and exposure (Marlow, et al., 2006).

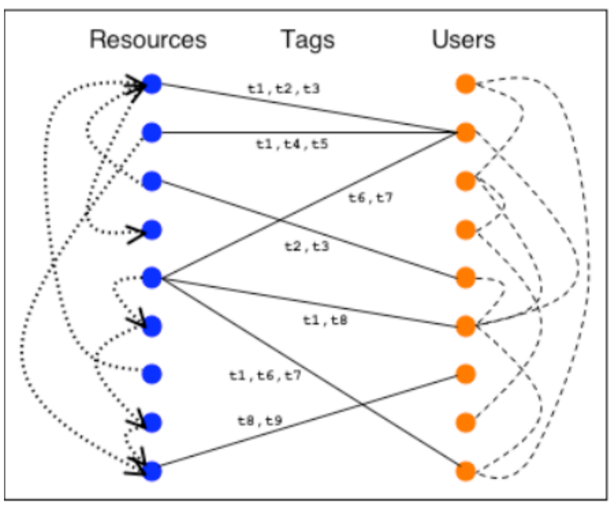


Fig 2.1 (Tagging system example) (Marlow, et al., 2006)

2.1.3 Automatic tagging

Automatic generation and recommendation of tags is achieved via exploiting the image content (Liu, et al., 2009). Different to manual tagging, automatic tagging is the automatic generation and assignment of image annotations to the digital image without user participation. These tags should describe the main image aspects and contents. Automatic tagging relies on different image aspects such as visual content and contextual information, solely or combined (Gu, et al., 2014).

Automatic tags are created as a result of examining image visual content. The difficulty facing automatic tagging systems is considering whether a tag is relevant or not, as the key task of such systems is the generation of relevant tags for the query image i.e. analyzed image). Resulting tags are often predictions and the key for successful tagging system is making these predictions as good as possible.

Some options for Automatic Image tagging systems:

1) Cloud Vision API: Rest API developed by google allowing developers to understand image content (Google LLC, 2018)
2) Microsoft Azure: Cognitive service allowing developers building application while adding cognitive features allowing interpretation of data and images based on machine learning.
3) Amazon rekognition: Based on deep learning, it allows for the analysis of any image and file. (Amazon, 2018)
4) Clarifai: AI Company specialized in visual recognition (clarifai, 2018)

This study will focus on using Google Vision API as the main tag generating system. Google vision was found relatively accurate and allows for free usage for certain image number in addition to the availability of documentations guiding API deployment. Studies were made comparing results of the systems and the choice of Google API was mainly favored. The result indicated Google vision API was best suited with regards to three aspects of accuracy, performance and cost; also Google services are highly maintained and consistently updated. (Filestack, 2017), (Grubhub bytes, 2017).

2.1.4 Semi- automatic tagging

Semi-automatic tag generation requires user assistance via providing one or more tag keywords after which generation of tags will commence (Sigurbjörnsson & Van Zwol, 2008). This approach depends upon manually producing a single accurate keyword, followed by semantic search of images using this keyword, then a visual content search is performed on the retrieved images, finally annotating the image with tags similar to the ones of the final search results (Wang, et al., 2006).

2.1.4 Semantic gap

As the study's concern is the comparison of automatic and manual tags, explanation of "semantic gap" or "data meaning gap" is necessary.
"The semantic gap is the lack of coincidence between the information that one can extract from the visual data and the interpretation that the same data have for a user in a given situation." (Smeulders, et al., 2000). It is mainly the difference in meaning formed within different representation systems (Hein, 2010). In other words, it is the lack of connection of between human information understanding and computer representation of same information. Users often desire deep and rich understanding and description of content while automatic systems extract only surface and shallow information (Li, et al., 2004).Text and words often have clear semantic meaning, but for image analysis, reflective thinking or critical thinking is required ,critical and reflective thinking is process of analyzing and making judgments regarding what has happened. Closing the sematic gap is one of the highly addressed image analysis and related topics, and a large amount of research has been performed addressing the topic (Datta, et al., 2008) (Smeulders, et al., 2000). Closing of the semantic tag sometimes happens indirectly as the tagging system competes in finding the largest number of relevant tags, the more relevant the tags are, the more successful the image tagging system.

2.1.5 Data source

The usage and analysis of images has been one of the human geography main research interest for the last two decades (Rose, 2016). Geographers analyzed the images in different sources, Images played major roles for understanding the meaning of space , such sources ranging from paintings (Cosgrove, 2017), maps (Cloud, 2003), photographs (Rose, 2008) (Schwartz & Ryan, 2003) and films (Cresswell, 2002). As more grew of the role of images and particularly photographs in describing and explaining the surrounding, the geographers began to focus on studying images and photographs (Latham & McCormack, 2009). As images and photos are shot at specific places, they are inherently spatial, and they provide the spatial information weather by attached geoformation coordinates or the location content analysis of the images (Crandall, et al., 2009).

Crowd sourcing is considered a new source for information retrieval, while it is new its relevancy to the spatial domain is increasing largely (Dunkel, 2015). Cell phones are becoming one of the main sensor of human behavior, as they become cheaper, more affordable and rich with user applications, they are penetrating every social level of society. Also mobile internet plans are becoming cheaper and internet wireless networks seems to be available everywhere, this caused for a shift to the usage of mobile social application such as Twitter, Instagram, Facebook and Flickr. These applications are used by the user on the go in any place at any time as the cellphones mobility property in its nature, therefore mapping large amount of human behavioral information with no restriction to place (Frias-Martinez, et al., 2012).

This study focuses on the usage of geo-tagged Flickr photos and its associated tags as the source of data for the study's comparison. Flickr is one of the most popular image sharing websites in the recent years and its tagging characteristic has been intensively studied over the years, also Flicker considers tags as the key piece to sharing, retrieval and discovery steps. (Liu, et al., 2009). On Flickr websites users tag their image In order for the general public to easily access (Ames & Naaman, 2007). Flickr allows for default easy public sharing and discovery of image, this aided the website in becoming a popular platform for image sharing (Marlow, et al., 2006).

Geo-referenced images must be collected for the comparison procedure of our area of interest. While collecting accurately geo-referenced images is important, such location directed platforms is avoided (Geograph, 2018). These platforms data does not represent truly human behavior, as their overall objective is mapping of certain locations (Dunkel, 2015).. As Flickr upload process for normal and georeferenced images is the same and not guided with mandatory specific rules, data from undirected platforms such as Flickr is a true representative for human behavior analysis (Antoniou, et al., 2010).

2.3 Performance evaluation and comparison

2.3.1 Relevancy

As stated, Image tagging is subjective and depends upon many variables such as culture, language, mood, experience and further variables (Greisdorf & O'Connor, 2002). Same situation applies when assessing generated tags relevancy. While some tags considered relevant according to one person, it is considered irrelevant to another.

Relevance importance is very obvious and considered as a base of information retrieval (Wang, et al., 2010). Relevance of retrieved tags is often measured in the terms of *Recall & Precision,* as these continue to be the most widely used commonly accepted metrics (Narasimhalu, et al., 1997), (Salton, 1971). As image tagging is the retrieval of content and information of the queried image, statistical measures from information retrieval (IR) such as precision and recall have been adopted and considered relevant in CBIR (Content based image retrieval) (Müller, et al., 2001).

Precision: Number of relative information found compared to the information retrieved, In other words number of relevant tags compare to the total number of tags; 1.0 is perfect score (Medelyan, et al., 2009).

Recall: Number of relative information retrieved compared to the total number of relative information available for retrieval. The number of relevant tags divided by the total of relevant tags. A perfect score is 1.0 and means that all the correct relevant tags meant to be found are found (Medelyan, et al., 2009). (See Eq.1 below)

Precision= No. of relevant tags/Total number of tags.

Recall= No. of relevant tags/ Expected number of tag.

Eq. 1 precision & recall

2.2 Related work

2.2.1 Google Image labeler

Google Image Labeler was a labeling process in the form of game aimed to improve quality and accuracy of google image search via harvesting information regarding images using crowd sourcing. It was online from 2006 till 2011 and relaunched in 2016.

Google Image labeler is based upon a type of game known as "ESP Game" (Von Ahn & Dabbish, 2004).The ESP game was firstly developed by "Luis Von Ahn". The game hands out similar images to two different paired players without means of communication other than knowledge of image labels, they have to agree on appropriate labels for this one image. The game aims to solve the problem of metadata creation. The idea was the usage of human knowledge (computational power of humans) for tasks that cannot be performed by computers. Google Licensed the ESP game and launched the game as a service of Google Image labeler (see fig2.1).

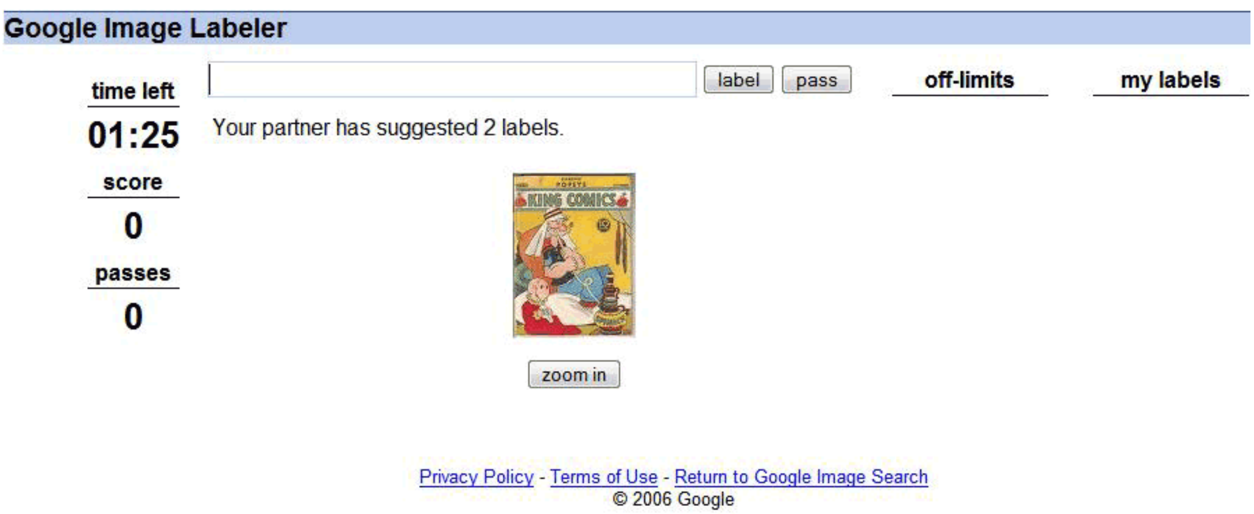


Fig 2.2 (Google Image Labeler)

2.2.2 Zone tag

Zone Tag is a public application made available for Nokia and Motorola phone users, which allows for the upload newly captured images directly to Flickr. Zone tag suggest some tag options, users then review the image and commence the upload step to Flickr. The user can choose or type in desired tags. Suggested tags are content-based suggestion retrieved from the Zone tag server, these tags are grouped into categories according to its sources (Local, recent, Zone tags or all). *(See fig 2.2)*

Local: Tags created by user, social network friends or tags created in user current location. *Recent tags*: Tags used in the last 24 hours. *Zone Tag*: system suggested tag from place and event database according to the user's physical location. The tags are ranked according to its frequency and likelihood measures (Ames & Naaman, 2007).

A user study was performed using Flickr and zone tag application, this study aimed to find the main motivation of tagging. Conclusion was drawn that people tag images to achieve higher functionality by making the search, browse and retrieval of images easy for themselves and others (Ames & Mor, 2007).

Fig 2.3 (zone tag application) (Ames & Naaman, 2007)

2.2.3 Visualization of the perceived environment

A study performed on Flick platform assessing the perception of emotion and social interaction of humans with reaction to the surrounding environment. The study visualize the perceptual response of people by collecting geotagged photos and analyzing their associated tags (Dunkel, 2015) , then study visualizes people's responses regarding the surrounding or the visited landscapes through the tags.

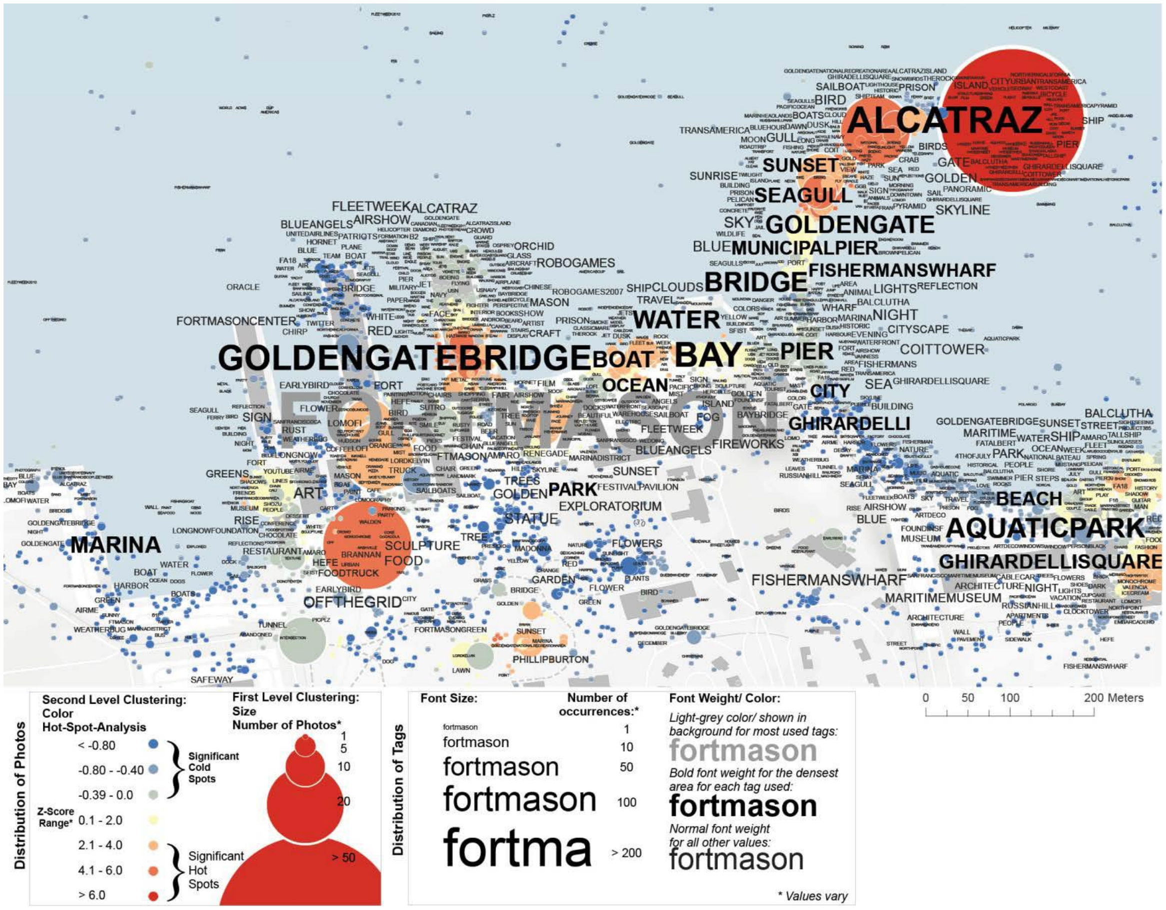


Fig 2.4. . Mapping of the Fort Mason area (Dunkel, 2015).

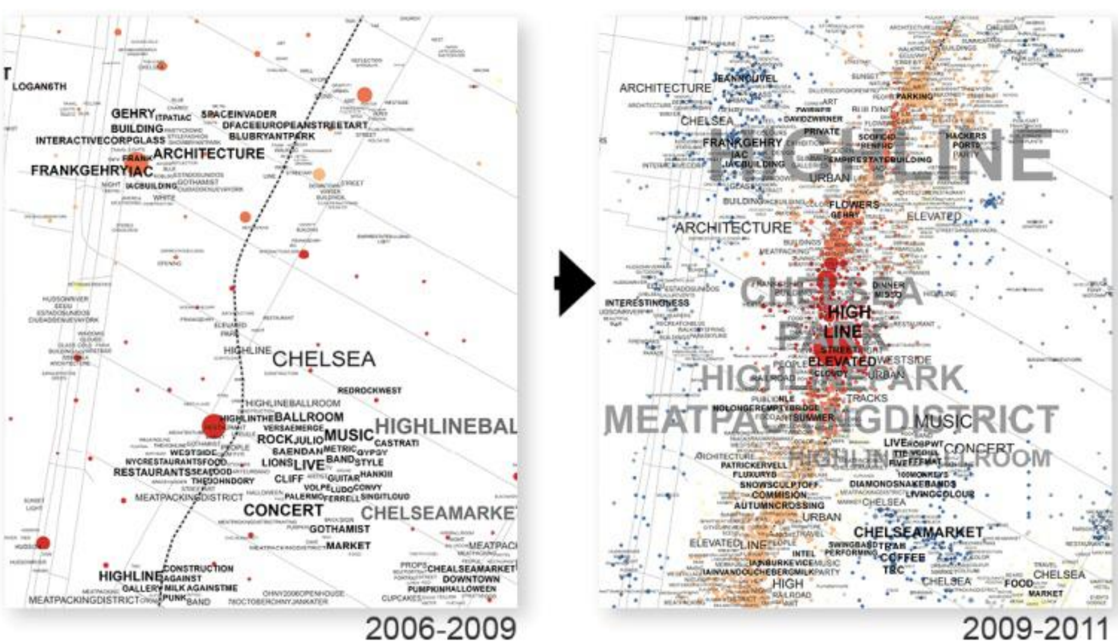


Fig 2.5 Map for the district of Chelsea (NY), (Dunkel, 2015).

Chapter 3: Approach & methodology

This chapter states and discuss the approach and methodology selected for addressing the study´s research questions. The first section of this chapter consists of the approach followed for determining and retrieving the relevant images from the sum of the image data supplied. The second section consist of the generation and processing of image tags and results. The third section discuss the visualization technique used for the final results visualization.

This chapter gives a detailed solution to the research question and explain the ideas and steps behind solution development. The results of each methodological step are presented in the results section and the developed code is attached in the appendix. Python scripting language is our main language for code scripting as it is a powerful and sophisticated tool for image processing.

Fig 3.1 below showing the followed workflow

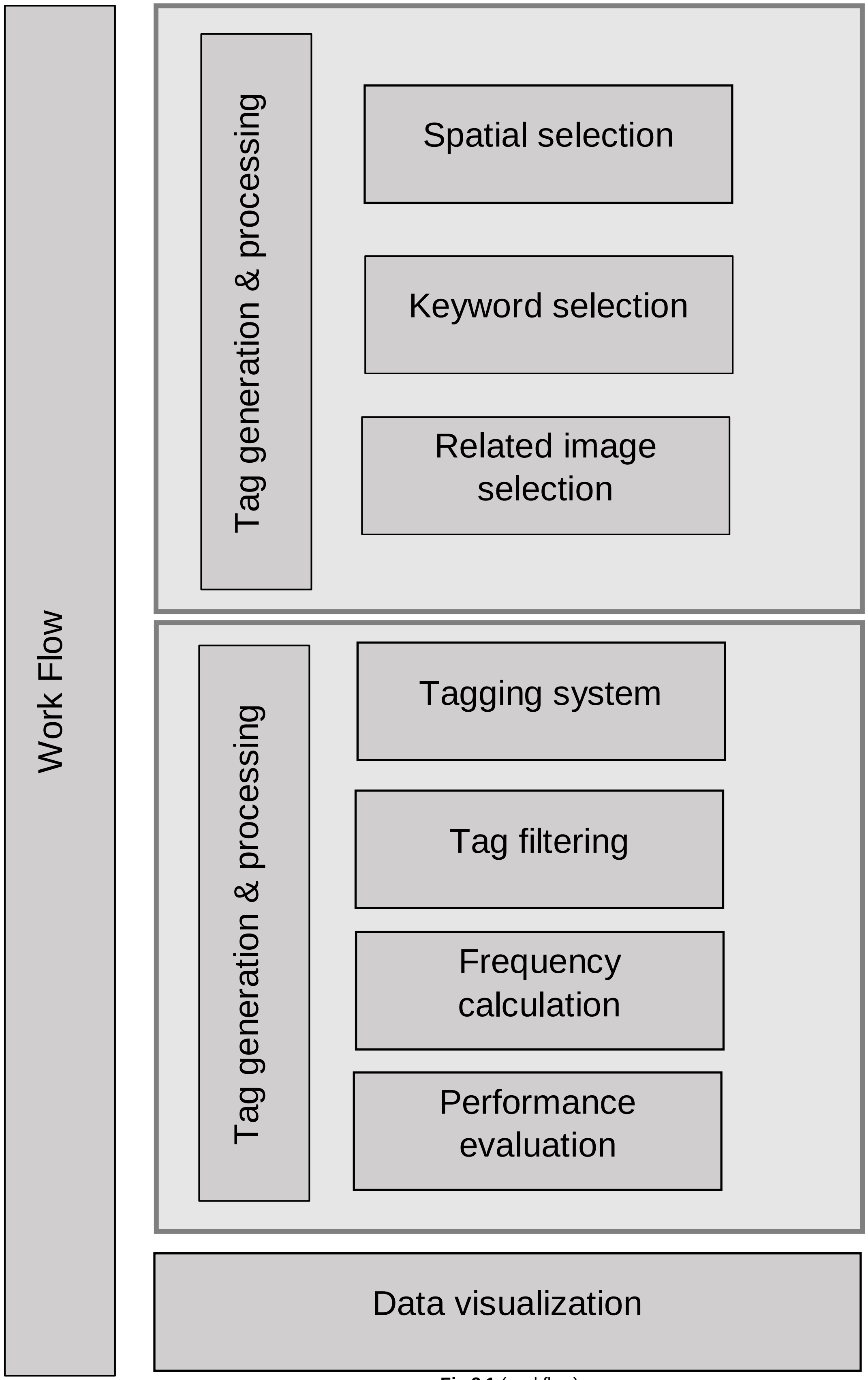


Fig.3.1 (workflow)

3.1 Data processing

Images from online image sharing portal (Flickr) is been used as the study's data source. Data was received from supervisor Alexander Dunkel, they are originally collected from Flickr's public API (application programming interface for automatic data accessing) and they represent entire Dresden.

The metadata consists of information regarding many aspects such as location: geotags, e.g. (latitude/longitude), upload time and further user-added information. The supplied information and data are stored in a MYSQL database.

3.1.1 Spatial Selection.

The location and position of the images are supplied as GPS coordinates in the format of latitude and longitude as well as other information regarding the image such as, but not limited to, image ID and name. The location coordinates mainly refer to the location of the camera or the phone used in the process of image capturing and images are principally automatically geo-tagged by the device at the time of capture. Location is automatically assigned as metadata after capture and the image is uploaded with this information. Users can also assign location to the image while uploading the image to the Flickr portal in run time. Flickr requests permission to access the GPS system associated with the capturing device and assign the location to the image, this process is known as geotagging. There are various sources of error regarding to the geotagging process, some of these are inaccurate GPS systems or incorrect calibratio

3.1.1.1 Study Area.

The bounding box set for the choice of images was the coordinates of Alaunpark and Grosser Garten with co-ordinates of (51.07361, 13.74930, 51.06871, 13.76152) (fig3.2) and (51.0457, 13.7369, 51.0281, 13.7881) (fig 3.3) respectively. This extent is a true representation of the area of interest (AOI). Images located within this extent are selected for further processing and tag generation. The result of this selection is a limited number of images. Increasing the bounding box size is tempting for an increase in data but, on the contrary, this increase in number affects the study and the comparison process negatively. The added images are regarded as noise or unwanted data as they are not a representation of activity within the desired park and do not fit within the study's main goal is the "Comparison of activity between user tags and automatically generated tags within parks".

Noise is a commonly used in the field of data mining and indicates the different effects for altering and distorting the data prior to its processing and evaluation. (Han, 2011). This spatial selection is performed using *PostgreSQL* for extracting places of interest.

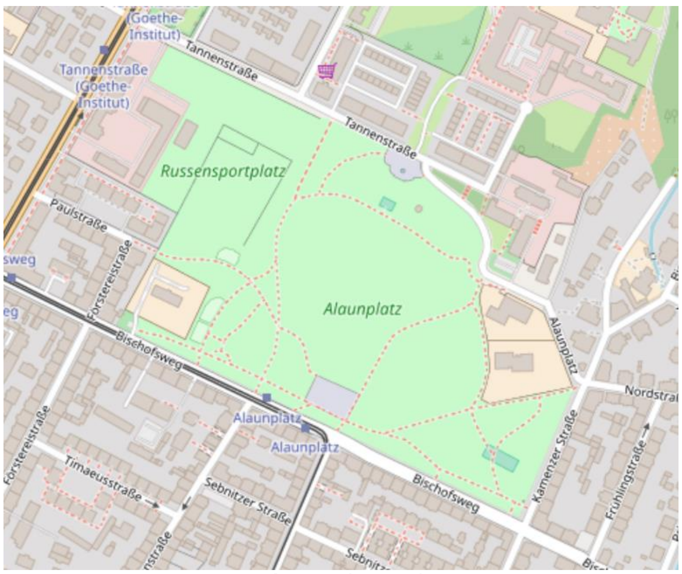


Fig 3.2 Alaunpark

Fig 3.3 Großergarten

3.1.3 Keyword Selection

Another applied criteria for selection is the usage of a tag keyword. Representation of the park name is often associated and assigned to the image as a tag word by the uploader. A word search of keywords (Alaunpark, Grossergarten, Alaun, and Großer) is used and the associated images are selected and added to the tag analysis process. This selection method is considered accurate, as the resulting selected images belong inside the area of interest and therefore successfully expand the number of images for the process of tag analysis.

The selection processes was performed using SQL command on the Meta data text files representing the whole of Dresden and the entire Flickr image library. The results of the selection was compiled in a CSV file containing only the desired images.
This will further filter some noisy images resulting from our previous selection.

3.1.2 Image Selection.

A python script was developed for this step which can be found in appendix (A). The idea of the script is to read the CSV output resulted from selection query and subsequently select the images represented in the file. The image name is used for matching and Image selection. Any image name existing in both image data folder and CSV file is selected and transferred to a new folder. The process result in a folder containing the images desired for both areas. This images are considered geographically relevant for our processing and study

3.2 Tag generation and processing

The image data supplied for the automatic tagging system (Google vision API) are now considered relevant and belong to our area of interest. The next step is to automatically generate the tags using Google API and furthermore, the generated tags is compared with regards to the tags assigned by the image owner.

3.2.1 Tagging System

Google vision API is selected API for the automatic tag generation as stated previously. The automatic tag generating system is scripted using *Python* language (attached in appendix A. The images are inputted to the system and tags are generated automatically using the *Rest API (Representational state transfer)*. Each generated tag has a rank or weight assigned by the API according to the tag word relevancy per the Vision API for each image. The tagging system developed script processes multiple images and their respective tag words are written to a text output file. The output file consists of image name and the respected tags and ranking of each tag (weight), the weight is displayed in the numbers below (1 is 100% match) (shown in fig 4.1)

```
Label Description            Label score
--------------------------------------------------------------------------------
images\12673546794_4da0a1d2e8_b.jpg
track  0.982165634632
transport  0.942794203758
tree  0.911194682121
rail transport  0.904377996922
plant  0.890832602978
leaf  0.889559626579
path  0.838963925838
woodland  0.785666525364
branch  0.74068582058
trail  0.738183021545
--------------------------------------------------------------------------------
images\12899482873_83c696613f_o.jpg
plant  0.976607859135
flower  0.969217538834
flowering plant  0.935333907604
spring  0.78786367178
tulip  0.670562028885
seed plant  0.519505083561
garden  0.508914589882
floristry  0.50003862381
--------------------------------------------------------------------------------
```

Fig 3.4 Automatic tag weight.

3.2.2 Comparison & performance evaluation

Information retrieval evaluation is proven to be a crucial problem in assessing the content-based image retrieval (CBIR) and content-based visual information retrieval (CBVIR). Researchers have driven and created various evaluation techniques (Müller, 2001), with evaluation of CBIR systems in earlier days being restricted for only printing (Flickner, et al., 1995) Positive impressions are expected since good queries with good results are only selected by developers.

The common information retrieval (IR) method for performance and evaluation are precision and recall with results usually being plotted in a graph as precision vs recall, this is called PR graph (Salton, 1971).The methodology used for performance evaluation is limited for precision calculations, as a recall variable is not suited for the impossibility to predict the number of relevant tags should have been found for each image.

Precision equals number of relevant tags divided by total number of tags found (See equation 1.1).A high precision score will prove that most of the tags found are relevant. A perfect precision score (1.00) means that all tags found are relevant.

Precision1= No. of relevant tags/Total number of tags. (eq. 1.1)

Recall= No. of relevant tags/ Expected number of tag. (eq.1.2)

Precision calculation requires tag relevancy assessment, this task is one of the most important and time consuming tasks (Müller, et al., 2001), as the tags relativity assessment is manually completed by human users and precision calculation is dependent upon assessment (Wang, et al., 2004).

The relevancy assessment is divided into 3 categories (relevant, non-relevant, and un-sure), due to the addition of a category *un-sure*, additional precision calculation is commenced.

Prescion2 = No. of relevant tags+ No. of unsure tags / Total number of tags. The results will be discussed in the next section.

Error calculation = No. of non-relevant tags / Total number of tags

Total Tags	12
Relevant	5
Non-relevant	2
Unsure	5
Percision1	0.417
Precision2	0.833
Error	0.167

Table (3.1) Performance evaluation calculation example.

For effective estimation of tagging system precision a study was performed asking participants for categorization of generated tags. Afterwards, precision was calculated and a graph was plotted illustrating the calculations. The results of this calculation will be presented and discussed in the next chapters.

3.2.3 Tag filtering

Tag filtering processes are carried out on both automatically generated and user assigned tags. The final output is a comparison of human activity mapping across greenspaces (Alaunpark and Großergarten). A python script is developed to match the output tags to an existing human activity library and select only the tags representing an activity. The output of this script is an activity list for both manual and automatic tags. In addition to the library matching, manual study is performed on produced tags for activity tag selection. Tag repetitions are manually resolved, as repetitions of some tags for different images exists, they mainly are uploaded by the same user.

Fig 3.5 Activity library (Rawson, 1999)

Recreational Activities	Leisure Activities	Hobbies
Backpacking	Attending auctions	Amateur radio
Baseball/softball	Attending auto races	Aquarium making
Basketball	Attending concerts	Arts and crafts
Billiards/playing pool	Attending plays	Astronomy
Bowling	Attending sports events	Auto repairing
Camping	Bicycling	Carpentry
Canoeing	Bird watching	Ceramics/pottery
Checkers	Coin collecting	Coaching Little League
Chess	Crossword puzzles	Computers
Dancing	Dining out	Cooking/baking
Golf	Driving	Electronics
Ice skating	Fishing	Flower arranging
Playing cards	Hiking	Gardening
Sailing/boating	Horseback riding	Genealogy
Shuffleboard	Listening to music	Home decorating
Skiing	Painting	Hunting
Skindiving	Picnics	Model building
Surfboarding	Playing video games	Photography
Swimming	Reading books	Playing music
Table tennis	Roller skating	Sewing
Touch football	Sightseeing	Singing
Volleyball	Sunbathing	Stained glass making
Weightlifting	Talking to friends	Volunteering
Other: ____________	Visiting museums	Woodworking
	Walks in parks	Other: ____________
	Watching movies and TV	
	Writing	
	Other: ____________	

Traditional activities

- Jogging
- Walking
- Bicycling
- Skating
- Swimming
- Weightlifting
- Nautilus-type workouts

Exercise classes

- Aerobics classes
- Jazz-aerobics
- Low-impact aerobics
- High-impact aerobics
- Step-aerobics classes
- Water-aerobics

Martial arts

- Judo
- Jujitsu
- Karate
- Kung-Fu
- Tai-Chi

Sports-type exercise

- Baseball
- Basketball
- Racquetball
- Roller hockey
- Softball
- Soccer
- Tennis
- Volleyball

Dance classes

- Ballet dancing
- Ballroom dancing
- Country and western
- Ethnic dancing
- Jazz dancing
- Latin dancing
- Modern dancing
- Swing dancing
- Tap dancing

Fig 3.5 Activity library (Rawson, 1999)

3.2.4 Frequency Calculation

Occurrences of tags (frequency) is calculated for the purpose of producing final outputs for data visualization. A python script is developed for calculating the frequency. The results are produced in a txt file which afterwards is exported and sorted in descending order to a CSV file. This is final output file is used for visualization.

The script is commenced on both filtered result files (automatic and manual tags). These files were produced in previous steps and represent activities for both manual and automatic tags of each park). The results are produced in a txt file afterwards and exported and sorted in descending order to a CSV file. This is the final output file used for visualization (fig4.2).

A	B
bunterepublikneustadt	130
musik	114
Live Band	123
schneeballschlacht	70
fest	56
picnik	4
biergarten	3
stadtfest	4
chill	1
fußball	1
geburtstag	1
party	1

Fig 3.6 final result example

3.3 Data visualization

Data visualization is the representation of data in a systematic form containing attributes and variables for an information unit (Khan & Khan, 2011).The visual representation goal is the minimalistic and easiest representation and interpretation of what is insight (Khan & Khan, 2011). It also provides a mental model of information (North, n.d.).

Statistical data are best represented using visual aspects, many conventional methods for data visualization are available for use. Methods vary and include pie charts, area charts, flow charts and even combination of charts, for example Venn diagrams or data flow diagrams.

Pie chart representation was found most convenient for the study's results representation. One study requiring subjects to detect quantities variations for different graphical figures (Pie chart & Bar chart), pie chart was found to be superior compared to bar chart as conclusions were driven faster (Eells, 1926).

This software used for statistical visualization is *tableau*. This software is used in generating charts and graphs for results .Furthermore maps of two parks were produced using *mapbox* and statistical analysis is embedded to the map using Photoshop .A pie chart map simply is combination of pie chart data with a map visualization. It is used for visualizing numerical data with location

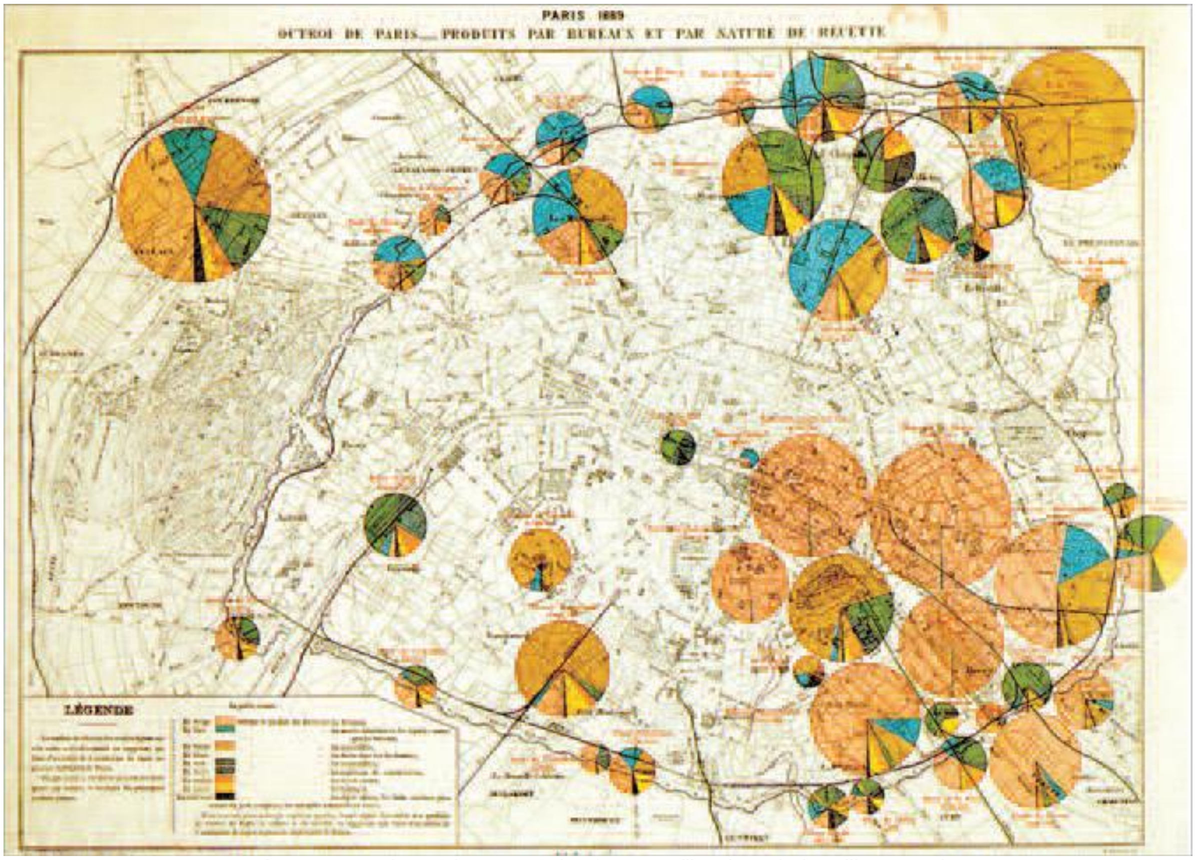


Fig 3.7 Examples of the use of pies from Bertillon (1891). (Bertillon, 1889)

Chapter 4: Results

This chapter presents the results derived for the research, it presents the result of each step commenced and concluding to comparison map between the activities driven via automatic tagging and assigned manual tags. The results presented as per work flow order

4.1 Relevant Image Selection

This section shows the results of the first methodology step which dealt with the selection of spatial relevant images for further processing.

SQL query was commenced upon the metadata in order to select the only relevant images belonging to Alaunpark and Großergarten. Metadata presented represents the whole of Dresden in four text files (fig 4.1). CSV files representing the relevant images belonging to our area of interest was a result of the spatial selection procedure (fig 4.2), (fig 4.3).

Dresden_Part1	6/28/2018 9:00 AM	Text Document	14,962 KB
Dresden_Part2	6/28/2018 9:00 AM	Text Document	12,789 KB
Dresden_Part3	6/28/2018 9:00 AM	Text Document	13,313 KB
Dresden_Part4	6/28/2018 9:00 AM	Text Document	608 KB

Fig (4.1) Meta-data

	A	B	C	D	E
1	filename	photoid	latitude	longitude	tags
2	176029718	1.76E+10	51.0715	13.75839	dresden;fuji;tsf;fujifilm;goethe;133;neustadt;alaunpark;x100;alaunplatz;goethewarauchhier;goethewarauchschonda
3	155039083	1.55E+10	51.07092	13.75675	street;autumn;dresden;herbst;streetphotography;neustadt;alaunpark;dresdenneustadt;alaunplatz
4	144378911	1.44E+10	51.07124	13.75512	germany;deutschland;dresden;saxony;sachsen;neustadt;alaunpark;alaunplatz;olympusomdem5;panasonicg20f17
5	997173617	9.97E+09	51.07188	13.75736	park;city;germany;garden;deutschland;dresden;nikon;day;cloudy;saxony;sachsen;stadt;grÃ¼n;garten;neustadt;alaunpark;d3200
6	828152263	8.28E+09	51.07102	13.75733	park;street;winter;light;people;blackandwhite;bw;snow;storm;black;cold;tree;broken;germany;deutschland;snowflakes;lights;dresden;blackwhite;couple;saxony;streetphotography;sachsen;schwarz;neus
7	778050565	7.78E+09	51.07125	13.75638	dresden;dresdner;neustadt;alaunpark;brn;bunte;republik;bokeh;grÃ¼n;menschen;freunde;3;sonnenbrille;portrait
8	683043551	6.83E+09	51.07341	13.75704	dresden;neubau;alaunpark;tannenstrasse
9	683043411	6.83E+09	51.07341	13.75704	dresden;neubau;alaunpark;tannenstrasse
10	694123109	6.94E+09	51.07129	13.75772	friends;sunset;beer;dresden;sonnenuntergang;bier;chill;freunde;entspannt;dresdner;neustadt;alaunpark;apark
11	686599452	6.87E+09	51.07086	13.75614	sun;dresden;alaunpark
12	701142225	7.01E+09	51.07088	13.75613	dresden;spring;alaunpark
13	697656669	6.98E+09	51.07341	13.75704	dresden;neubau;alaunpark;tannenstrasse
14	697656398	6.98E+09	51.07341	13.75704	dresden;neubau;alaunpark;tannenstrasse
15	697656173	6.98E+09	51.07341	13.75704	dresden;neubau;alaunpark;tannenstrasse
16	683043219	6.83E+09	51.07341	13.75704	dresden;neubau;alaunpark;tannenstrasse
17	604320303	6.04E+09	51.07093	13.75681	dresden;nebel;parc;slackline;neustadt;alaunpark;ceata
18	589257651	5.89E+09	51.07147	13.75779	music;metal;dresden;live;musik;fest;stonehead;stoner;neustadt;bÃ¼hne;brn;alaunpark;2011;bunterepublikneustadt;merkwÃ¼rden;deathrite
19	589257640	5.89E+09	51.07147	13.75779	music;metal;dresden;live;musik;fest;stonehead;stoner;neustadt;bÃ¼hne;brn;alaunpark;2011;bunterepublikneustadt;merkwÃ¼rden;deathrite
20	589257631	5.89E+09	51.07147	13.75779	music;metal;dresden;live;musik;fest;stonehead;stoner;neustadt;bÃ¼hne;brn;alaunpark;2011;bunterepublikneustadt;merkwÃ¼rden;deathrite
21	589257625	5.89E+09	51.07147	13.75779	music;metal;dresden;live;musik;fest;stonehead;stoner;neustadt;bÃ¼hne;brn;alaunpark;2011;bunterepublikneustadt;merkwÃ¼rden;deathrite
22	589200844	5.89E+09	51.07147	13.75779	music;metal;dresden;live;musik;fest;stonehead;stoner;neustadt;bÃ¼hne;brn;alaunpark;2011;bunterepublikneustadt;merkwÃ¼rden;deathrite
23	589257607	5.89E+09	51.07147	13.75779	music;metal;dresden;live;musik;fest;stonehead;stoner;neustadt;bÃ¼hne;brn;alaunpark;2011;bunterepublikneustadt;merkwÃ¼rden;deathrite
24	589257597	5.89E+09	51.07147	13.75779	music;metal;dresden;live;musik;fest;stonehead;stoner;neustadt;bÃ¼hne;brn;alaunpark;2011;bunterepublikneustadt;merkwÃ¼rden;deathrite
25	589257589	5.89E+09	51.07147	13.75779	music;metal;dresden;live;musik;fest;stonehead;stoner;neustadt;bÃ¼hne;brn;alaunpark;2011;bunterepublikneustadt;merkwÃ¼rden;deathrite
26	589257581	5.89E+09	51.07147	13.75779	music;metal;dresden;live;musik;fest;stonehead;stoner;neustadt;bÃ¼hne;brn;alaunpark;2011;bunterepublikneustadt;merkwÃ¼rden;deathrite
27	589200800	5.89E+09	51.07147	13.75779	music;metal;dresden;live;musik;fest;stonehead;stoner;neustadt;bÃ¼hne;brn;alaunpark;2011;bunterepublikneustadt;merkwÃ¼rden;deathrite

DresdenPart1(Alaun)

Ready

Fig 4.2(Alaunpark images)

	A	B	C	D	E
1	134785849	1.35E+10	51.053638	13.74081	texture;photomanipulation;germany;dresden;palais;grossergartendresden
2	521293245	5.21E+09	51.053638	13.74081	flower;dresden;grossergarten
3	498728659	4.99E+09	51.053638	13.74081	park;germany;dresden;saxony;engine;railway;steam;sachsen;garten;grosser;liliput;parkeisenbahn;liliputeisenbahn
4	498790322	4.99E+09	51.053638	13.74081	park;germany;dresden;gate;crossing;saxony;railway;sachsen;garten;grosser;liliput;schranke;parkeisenbahn;bahnÃ¼bergang;liliputeisenbahn
5	503042675	5.03E+09	51.053638	13.74081	park;germany;dresden;saxony;railway;sachsen;garten;grosser;liliput;parkeisenbahn;liliputeisenbahn
6	498710614	4.99E+09	51.053638	13.74081	park;germany;dresden;saxony;railway;sachsen;garten;grosser;liliput;parkeisenbahn;liliputeisenbahn
7	472872489	4.73E+09	51.053638	13.74081	park;germany;dresden;saxony;railway;sachsen;garten;grosser;liliput;parkeisenbahn;liliputeisenbahn
8	472806848	4.73E+09	51.053638	13.74081	park;germany;dresden;saxony;railway;sachsen;garten;grosser;liliput;parkeisenbahn;liliputeisenbahn
9	472871241	4.73E+09	51.053638	13.74081	park;germany;dresden;saxony;railway;sachsen;garten;grosser;liliput;parkeisenbahn;liliputeisenbahn
10	503036677	5.03E+09	51.053638	13.74081	park;germany;dresden;saxony;railway;sachsen;garten;grosser;liliput;parkeisenbahn;liliputeisenbahn
11	498651566	4.99E+09	51.053638	13.74081	park;germany;dresden;saxony;railway;sachsen;garten;grosser;liliput;parkeisenbahn;liliputeisenbahn
12	470858698	4.71E+09	51.054374	13.82002	panorama;dresden;autobahn;17;kraftwerk;wu;brÃ¼cke;rathaus;tu;altstadt;frauenkirche;garten;sÃ¼dvorstadt;grosser;innenstadt;hofkirche;prohlis;hochhÃ¤user;kreuzkirche;dreikÃ¶nigskirche;blasewitz;
13	515164155	5.15E+09	50.987827	13.85942	garten;grossergarten;grossergartenherbstdresdenpark
14	372645558	3.73E+10	51.038061	13.76168	palais;grossergarten;dresden;elbflorenz;moonlight;sachsen;saxony;germany
15	144276444	1.44E+10	51.038518	13.7625	dresden;dresdengrossergarten;olympuszuikodigitaled1442mmf3556
16	144296721	1.44E+10	51.038518	13.7625	dresden;dresdengrossergarten;olympuszuikodigitaled1442mmf3556
17	142443803	1.42E+10	51.038518	13.7625	dresden;dresdengrossergarten;olympuszuikodigitaled1442mmf3556
18	852320140	8.52E+09	51.037724	13.76364	germany;garden;deutschland;dresden;europe;palace;palais;garten;grosser
19	832511833	8.33E+09	51.039383	13.76162	park;winter;dresden;feeding;impressionen;dezember;garten;grosser;coaltit;groser;kohlmeise;handfÃ¼tterung;birdsfÃ¼tterung
20	768463652	7.68E+09	51.03783	13.76288	flowers;red;rot;closeup;catchycolors;germany;deutschland;dresden;europa;tulips;blossom;saxony;natur;blumen;exhibition;sachsen;palais;garten;ausstellung;tulpen;grossergarten;groser
21	744065727	7.44E+09	51.03783	13.76288	flowers;blue;red;rot;catchycolors;germany;geotagged;deutschland;dresden;europa;blossom;saxony;natur;blumen;exhibition;sachsen;palais;hydrangea;blau;garten;ausstellung;blÃ¼ten;hortensie;grosser
22	740218279	7.4E+09	51.03783	13.76288	flowers;window;germany;geotagged;deutschland;dresden;europa;view;fenster;saxony;natur;blossoms;blumen;exhibition;sachsen;palais;garten;ausblick;ausstellung;allee;blÃ¼ten;grossergarten;groser;q
23	737908167	7.38E+09	51.03783	13.76288	flowers;catchycolors;germany;geotagged;deutschland;dresden;europa;saxony;natur;blossoms;violet;blumen;lila;sachsen;palais;garten;ausstellung;violett;blÃ¼ten;grossergarten;groser;dresdnerfrÃ¼hling
24	727987846	7.28E+09	51.037855	13.76284	flowers;autumn;square;dresden;squareformat;garten;hefe;grosser;iphoneography;instagramapp
25	697212520	6.97E+09	51.038479	13.76278	schweiz;dresden;elba;sachsen;frauenkirche;elbe;meissen;alte;meister;semperoper;dresda;gemaeldegalerie;grossergarten;saechsische
26	703189109	7.03E+09	51.037884	13.76298	flowers;catchycolors;germany;geotagged;deutschland;dresden;tulips;saxony;blossoms;blumen;exhibition;sachsen;palais;ausstellung;tulpen;blÃ¼ten;grossergarten;geo:lat=51037884;geo:lon=13762983
27	694514612	6.95E+09	51.037724	13.76295	alex;dresden;dr;palais;garten;barock;ausstellung;grosser;2012;frÃ¼hling;neues;dresdner;rollrasen

Fig4.3 (Großergarten images)

For relevant image selection from the handed data a python script was applied to the image folder (data folder) and relevant images were selected and transferred to a new folder. This folder contains only relevant images for (Alaun Park and Großergarten).

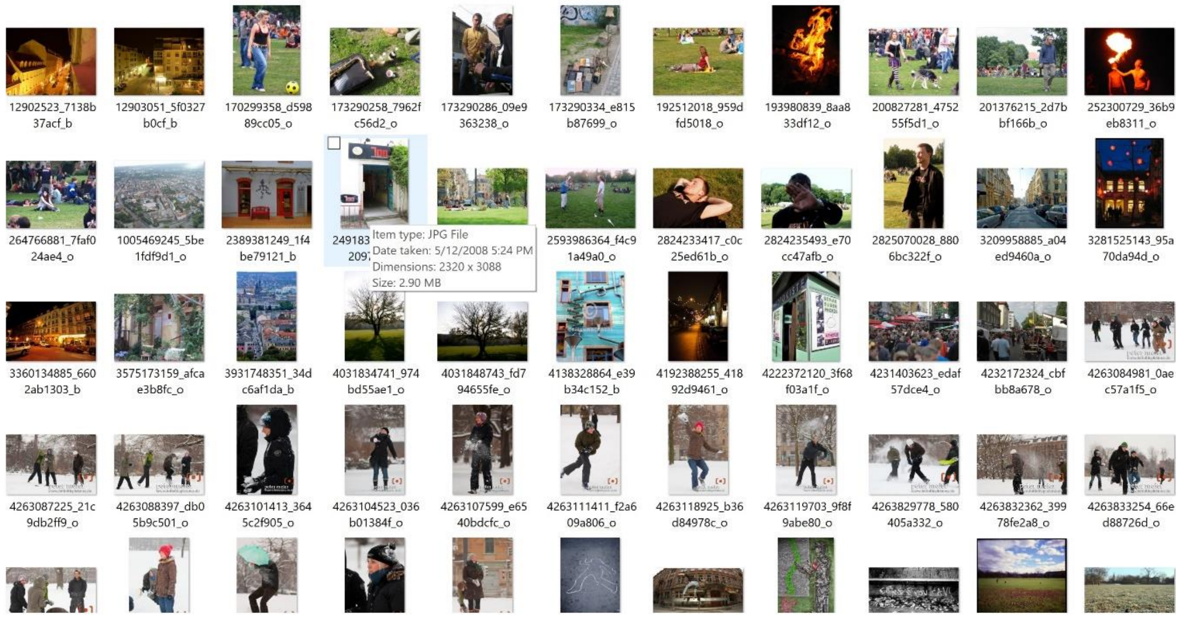


fig4.4 (Alaunpark images)

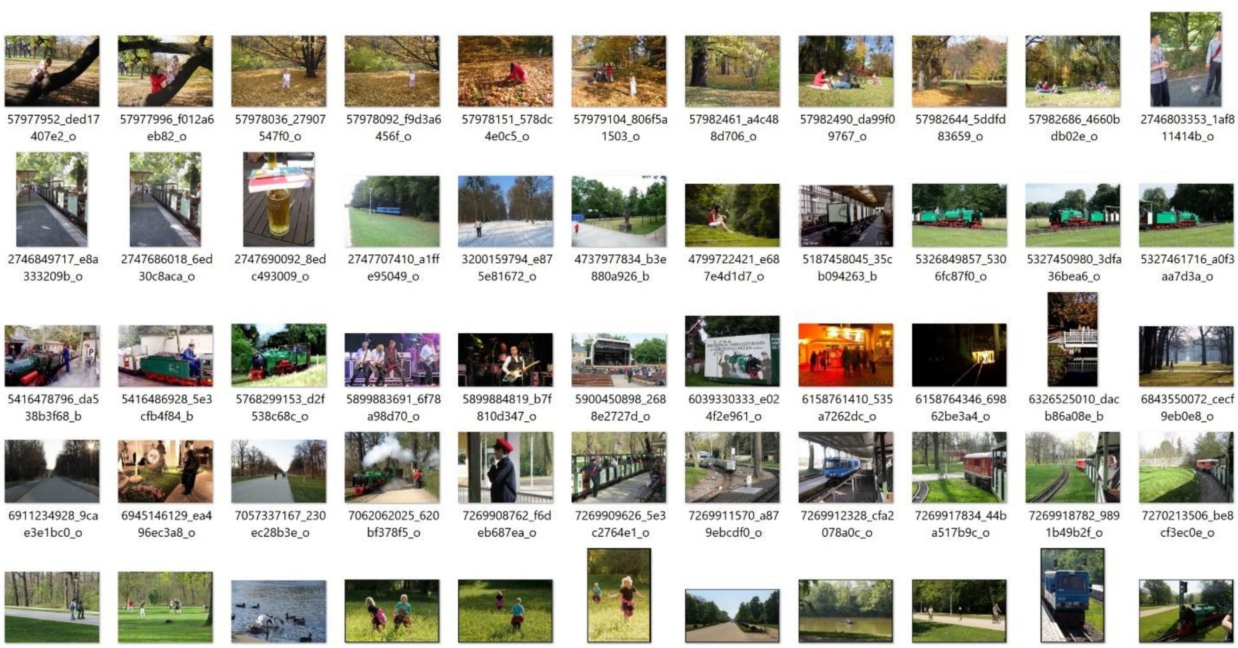


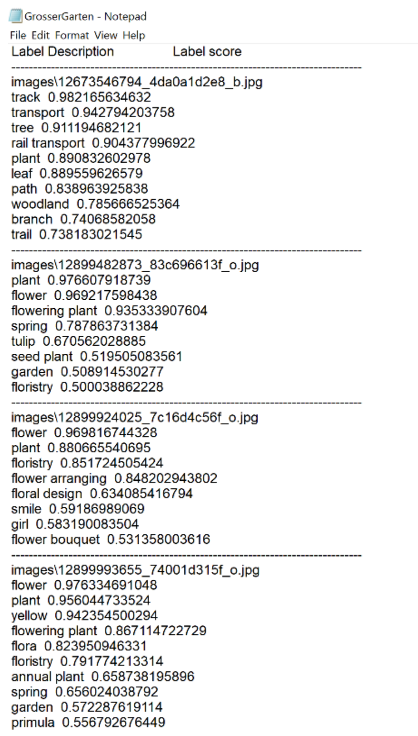
fig4.5 (Großergarten images)

4.2 Tag generation

This step works on the filtered data resulted from the previous step. Google API is used for the generation of tags (automatic tagging). Python script is developed based up Google vision API that generates the tags for the selected images. The result is a text file containing the tags for each area of interest (Fig4.6)

```
Alaunpark - Notepad
File Edit Format View Help
--------------------------------------------------------------------------------
images\57982490_da99f09767_o.jpg
people  0.962286472321
plant  0.942930519581
grass  0.897629797459
tree  0.895204603672
outdoor recreation  0.872732162476
lawn  0.796830534935
leaf  0.779382348061
leisure  0.766590833664
recreation  0.756604731083
picnic  0.756259083748
--------------------------------------------------------------------------------
images\57982644_5ddfd83659_o.jpg
leaf  0.96760314703
tree  0.95379036665
nature  0.949847698212
autumn  0.931060373783
woody plant  0.887177765369
grove  0.883515000343
grass  0.844396531582
plant  0.841172575951
park  0.807897150517
woodland  0.806562721729
--------------------------------------------------------------------------------
images\57982686_4660bdb02e_o.jpg
land vehicle  0.969310522079
plant  0.950810790062
tree  0.939267456532
woody plant  0.898228406906
bicycle  0.84938621521
outdoor recreation  0.791299939156
grass  0.790618896484
path  0.746788620949
vehicle  0.737251937389
woodland  0.727994024754
--------------------------------------------------------------------------------
images\5899883691_6f78a98d70_o.jpg
performance  0.927974283695
musician  0.925606608391
stage  0.877421319485
music  0.86373847723
entertainment  0.83556085825
music artist  0.783744394779
concert  0.77601981163
```

Fig4.6 (Alaunpark generated tags).



```
GrosserGarten - Notepad
File Edit Format View Help
Label Description          Label score
--------------------------------------------------------------------------------
images\12673546794_4da0a1d2e8_b.jpg
track  0.982165634632
transport  0.942794203758
tree  0.911194682121
rail transport  0.904377996922
plant  0.890832602978
leaf  0.889559626579
path  0.838963925838
woodland  0.785666525364
branch  0.74068582058
trail  0.738183021545
--------------------------------------------------------------------------------
images\12899482873_83c696613f_o.jpg
plant  0.976607918739
flower  0.969217598438
flowering plant  0.935333907604
spring  0.787863731384
tulip  0.670562028885
seed plant  0.519505083561
garden  0.508914530277
floristry  0.500038862228
--------------------------------------------------------------------------------
images\12899924025_7c16d4c56f_o.jpg
flower  0.969816744328
plant  0.880665540695
floristry  0.851724505424
flower arranging  0.848202943802
floral design  0.634085416794
smile  0.59186989069
girl  0.583190083504
flower bouquet  0.531358003616
--------------------------------------------------------------------------------
images\12899993655_74001d315f_o.jpg
flower  0.976334691048
plant  0.956044733524
yellow  0.942354500294
flowering plant  0.867114722729
flora  0.823950946331
floristry  0.791774213314
annual plant  0.658738195896
spring  0.656024038792
garden  0.572287619114
primula  0.556792676449
```

(Großergarten generated tags).

4.3 Comparison & Performance evaluation

A survey was performed for comparison and performance evaluation. The participants were asked for the categorization of the system generated tags. The survey's final results, question example and response are presented below (fig 4.7, fig 4.8), complete survey is attached in appendix. The visualization indicates the average precision along each question and total precision average. Graph with drawn outlining the precision along images from the answers collected from the survey (fig 4.1

1. Alaunpark

1. Please Check which tags are (Relevant, Non-relevant, unsure If you cannot decide) of the image below.

	Relevant	Non-relevant	Unsure
Woman	X		
mammal	X		
vertebrate			X
fun	X		
girl	X		
grass	X		
plant	X		
public event	X		
recreation			X
summer	X		

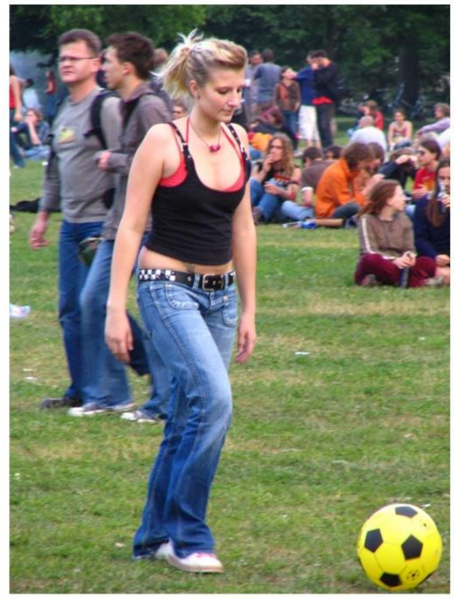


Fig4.7 Question example

1. Alaunpark

1. Please Check which tags are (Relevant, Non-relevant, unsure If you cannot decide) of the image below.

	Relevant	Non-relevant	Unsure
Woman			
mammal			
vertebrate			
fun			
girl			
grass			
plant			
public event			
recreation			
summer			

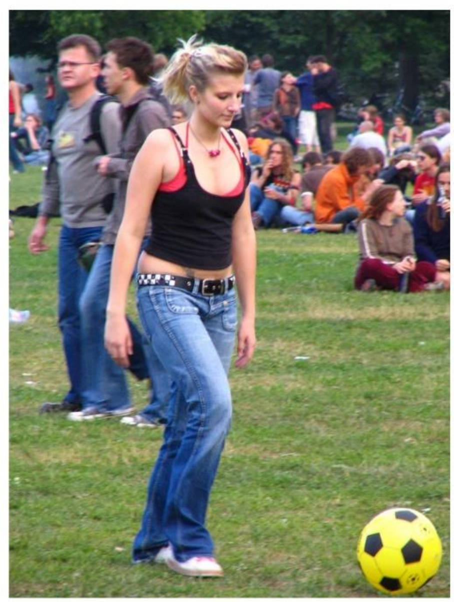


Fig4.8 Response example.

Q2	Relavant	Nonrelavant	Unsure	Precision1	Precision2	Error
Mammal	5	5	0	0.5	0.5	0.5
Grass	10	0	0	1	1	0
Vertebrate X	2	7	1	0.2	0.3	0.7
Lawn X	8	1	1	0.8	0.9	0.1
play X	3	3	4	0.3	0.7	0.3
fun X	7	0	3	0.7	1	0
outdoor recreation	10	0	0	1	1	0
recreation X	9	1	0	0.9	0.9	0.1
summer	10	0	0	1	1	0
Mean Precision1				0.711111111		
Mean Precision2					0.811111111	
Mean Error						0.188889

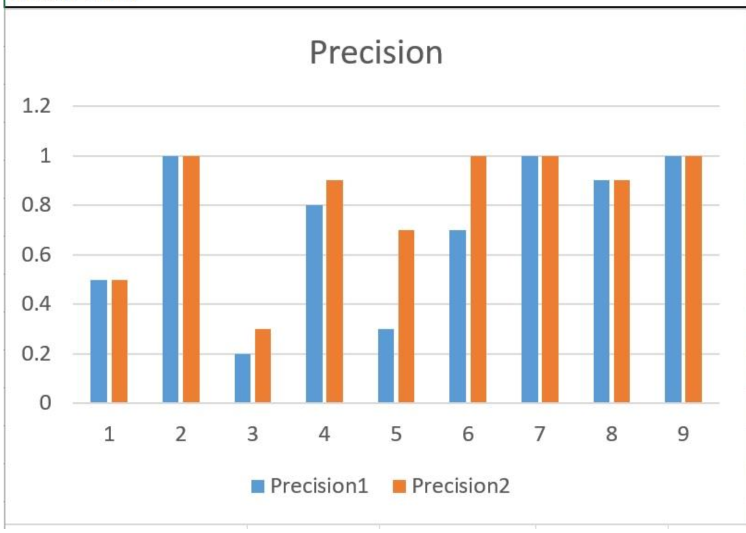


Fig 4.9 (Survey answer example)

The figure above represents collected survey answers for question 2 and it is calculated precision and error. The collected answers for the survey lead to plotting of average precision calculation for the tag generation system (see fig4.10, 4.11).

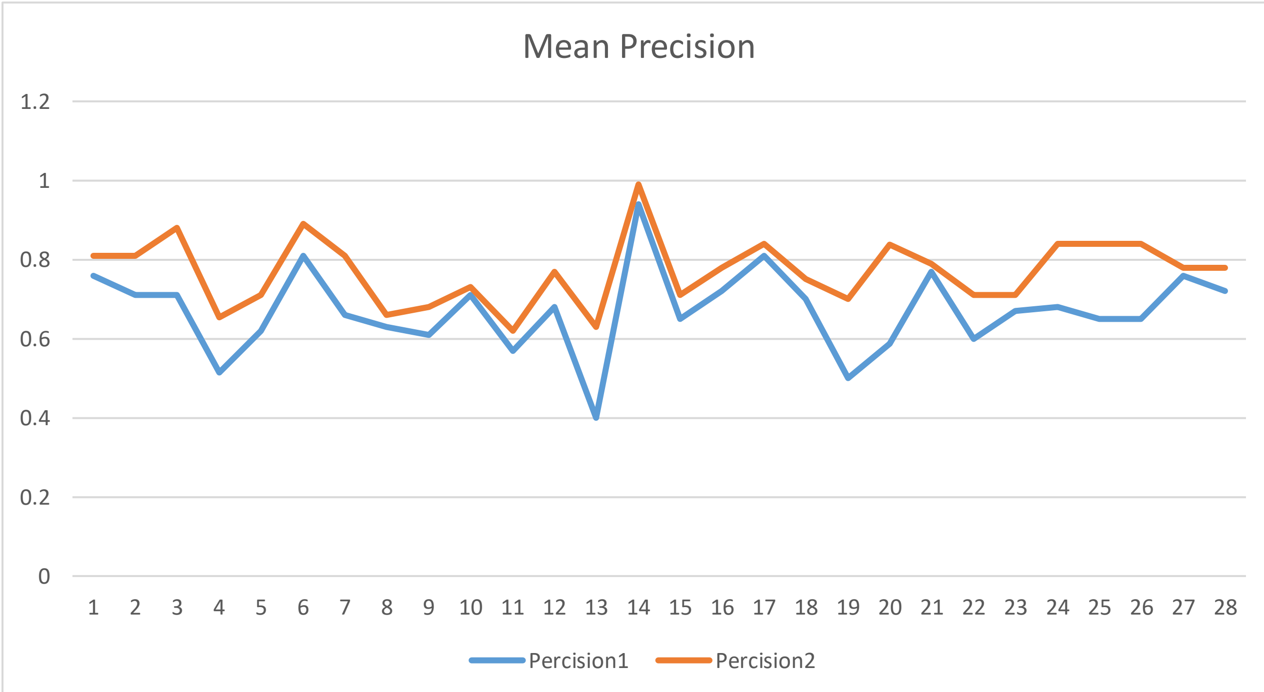


Fig 4.10 (Mean Precision)

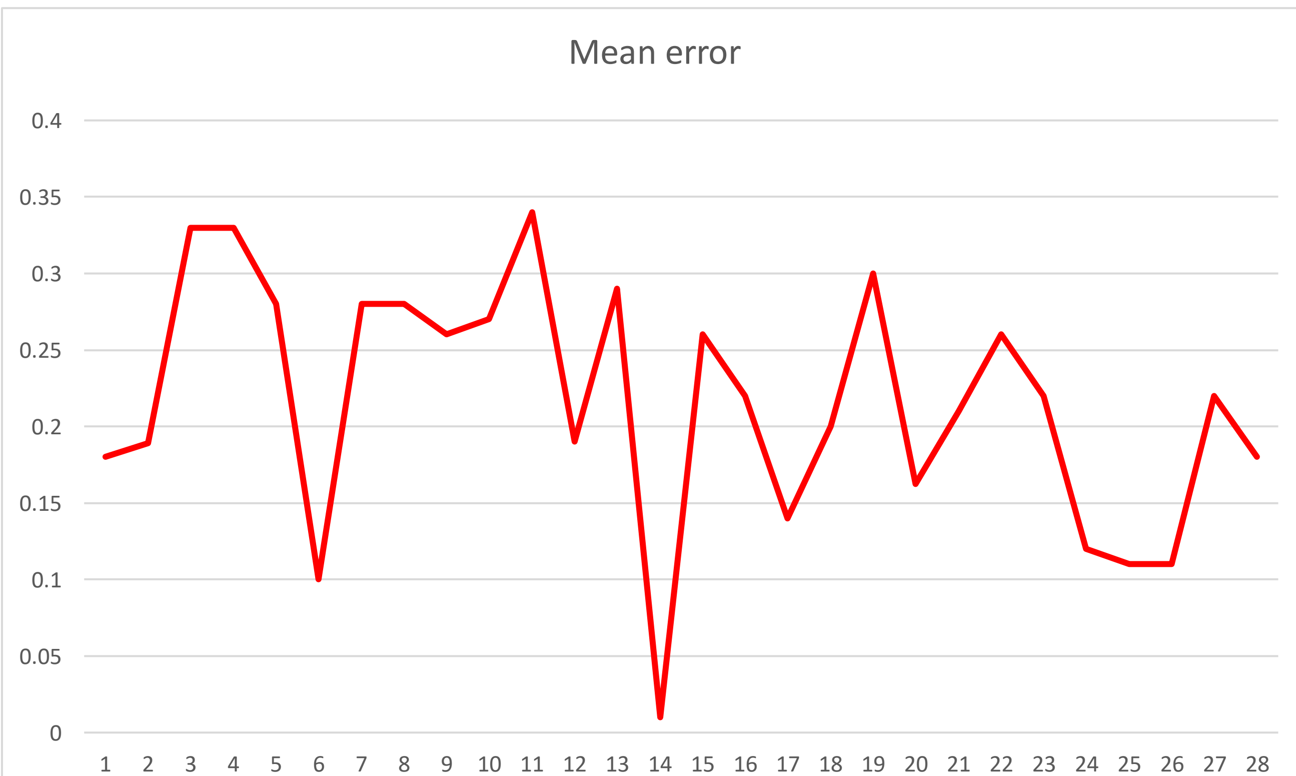


Fig 4.11 Mean error

4.4 Frequency calculation &Tag filtering

As stated in previous section, human activities libraries was used in tag filtration, as the study is interested only in tags representing an activity. In addition repetition was removed as they are considered noise. The results were produced using the developed python scripts.

4.4.1 Alaunpark

Tag Name	Frequency
dresden	113
neustadt	53
alaunstrase	50
germany	40
alaunpark	39
deutschland	29
alaunplatz	23
sachsen	20
alemania	19
saxony	17
brn	15
alaunstrasse	12
dresdenneustadt	11
street	11
park	9
9mai	8
geotagged	8
streetart	7
sonnenuntergang	6
strase	6
winter	6
alemanha	5
allemagne	5
architecture	5
canon	5
duitsland	5

Fig4.12 Manual tags-unfiltered Alaunpark)

Tag Name	Frequency
brn	15
picnik	5
musik	5
bierTrinken	4
bunterepublikneustadt	3
deathrite	2
fest	2
fireeater	2
smoking	2
football	2
fotografering	2
schneeballschlacht	2
relax	2
akrobat	1
backgammon	1
essen	1
frisbee	1
geburtstag	1
party	1

Fig4.13 Manual tags-filtered Alaunpark

Tag Name	Frequeny
winter	41
fun	40
ice	31
plant	28
performance	27
concert	26
tree	26
snow	25
music	24
event	23
freezing	23
grass	21
musician	19
entertainment	18
instrument	17
recreation	17
girl	15
headgear	13
footwear	12
singing	12
stage	11
arts	10
darkness	10

Fig4.14 Automatic tags unfiltered Alaunpark

Tag	Frequency
fun	40
performance	27
concert	26
music	32
event	23
entertainment	18
recreation	17
singing	12
arts	10
performing	10
photography	9
sport	9
art	8
sports	4
social	2
leisure	1
party	1
picnic	1
show	1
leisure	1
obedience	1

Fig 4.15 Automatic tags-filtered Alaunpark.

4.4.2 Großergarten

Tags	Frequency
dresden	140
grosergarten	84
deutschland	71
germany	64
sachsen	63
saxony	50
grossergarten	44
park	25
garten	22
geotagged	22
botanischergarten	19
garden	16
zoo	15
europa	13
parkeisenbahn	13
blumen	11
catchycolors	11
dresdnerparkeisenbahn	11
europe	10
flowers	10
gläsernemanufaktur	10
animalplanet	9
groser	9
brunnen	8
city	8
liliputbahn	8

Fig 4.16 Manual tags-unfiltered Großergarten.

Tags	Frequency
plant	99
tree	63
transport	48
flower	33
grass	30
nature	30
vehicle	26
leaf	21
train	20
track	19
rail	18
woody	18
rolling	17
stock	17
car	16
floristry	16
garden	16
green	14
sky	14
spring	14
water	14
flora	13
recreation	13
path	12
public	11
flowering	10

Fig4.17 automatic tags-Unfiltered Großergarten.

Tags	Frequency
sightseeing	6
classiccars show	5
adventsfahrten	3
hobbyphotograph	3
vacation	3
relax	2
music	2
biergarten	1
fridaymarket	1

Fig 4.18 Manual tags-filtered Großergarten.

Tags	Frequency
rolling	17
floristry	26
recreation	13
fun	6
tourism	12
artwork	4
leisure	3
music	5
skiing	2
sport	3
beer	1
competition	1
cycle	1
picnic	1
play	1
sitting	1
tournament	1
walking	1

Fig4.19 Automatic tags-filtered Großergarten.

4.5 Data visualization

The filtered tags represents the study´s final results. The visualization aim to present the result in a simple form for the comparison of activity tags assigned by users and automatically generated in Alaunpark and Großergarten. Firstly results are represented by a tree map figure showing the activities taking place in parks accompanied with a combined tags bar chart. Afterwards a map is generated presenting the study results.

4.5.1 Alaunpark

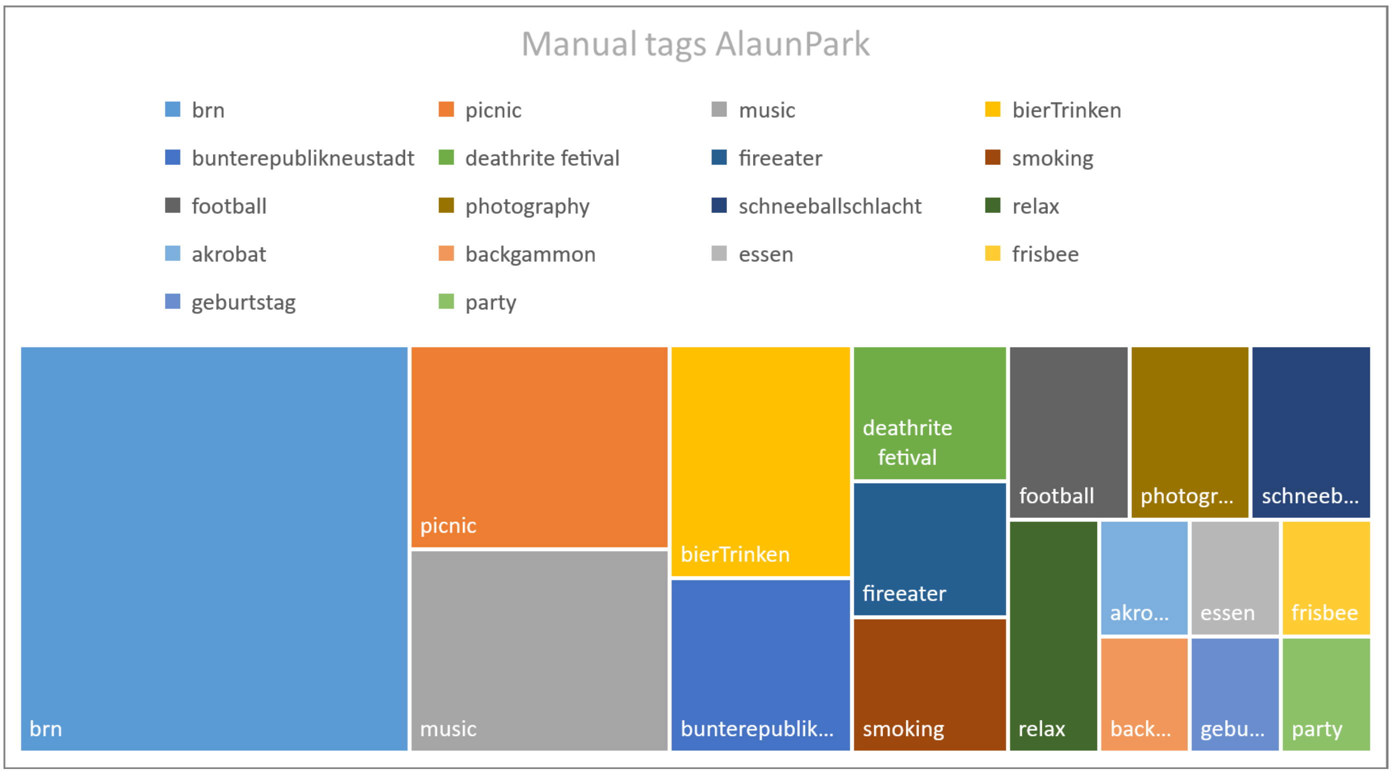


Fig 4.20 (Alaunpark manual assigned tag)

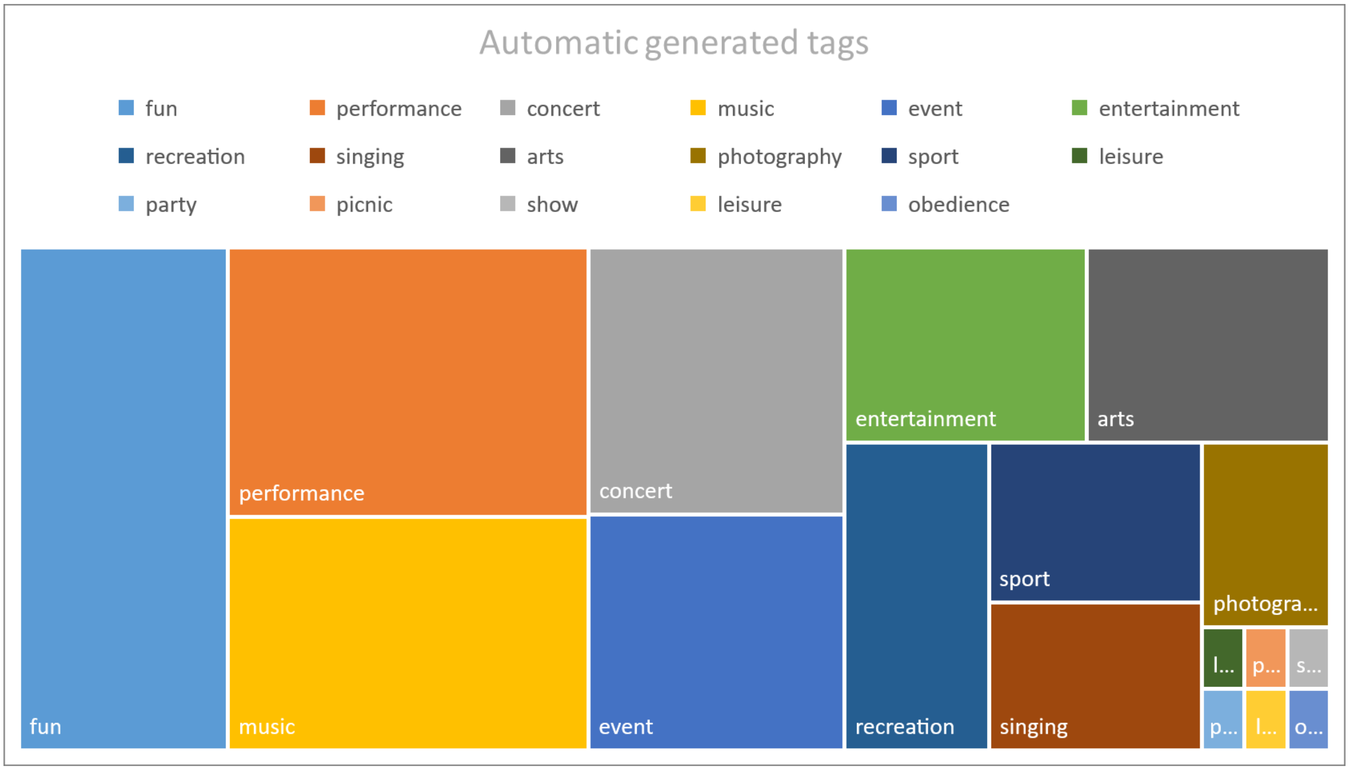


Fig 4.21 Alaunpark automatically generated tags

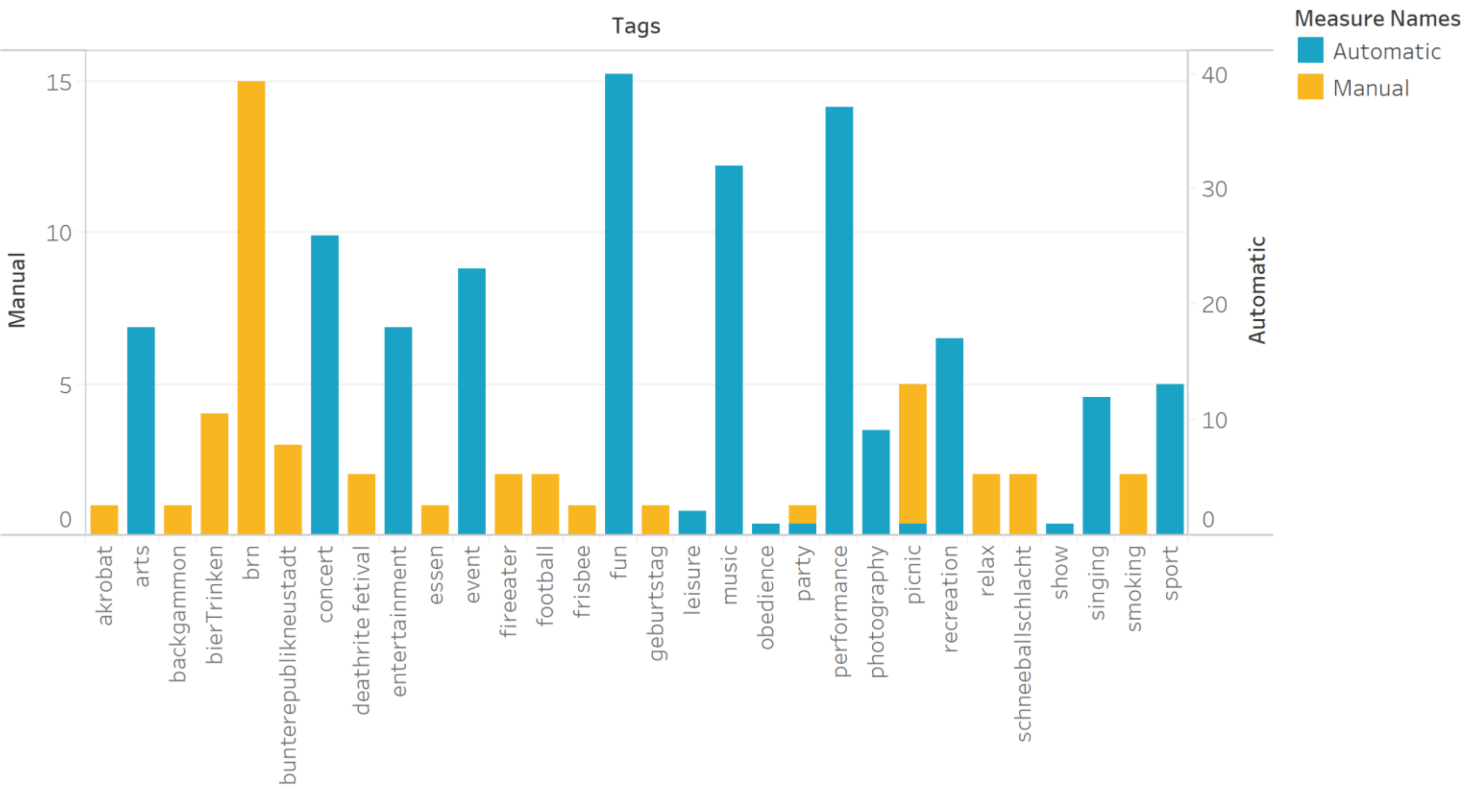


Fig 4.22 Manual & Automatic tags

4.5.2 Großergarten

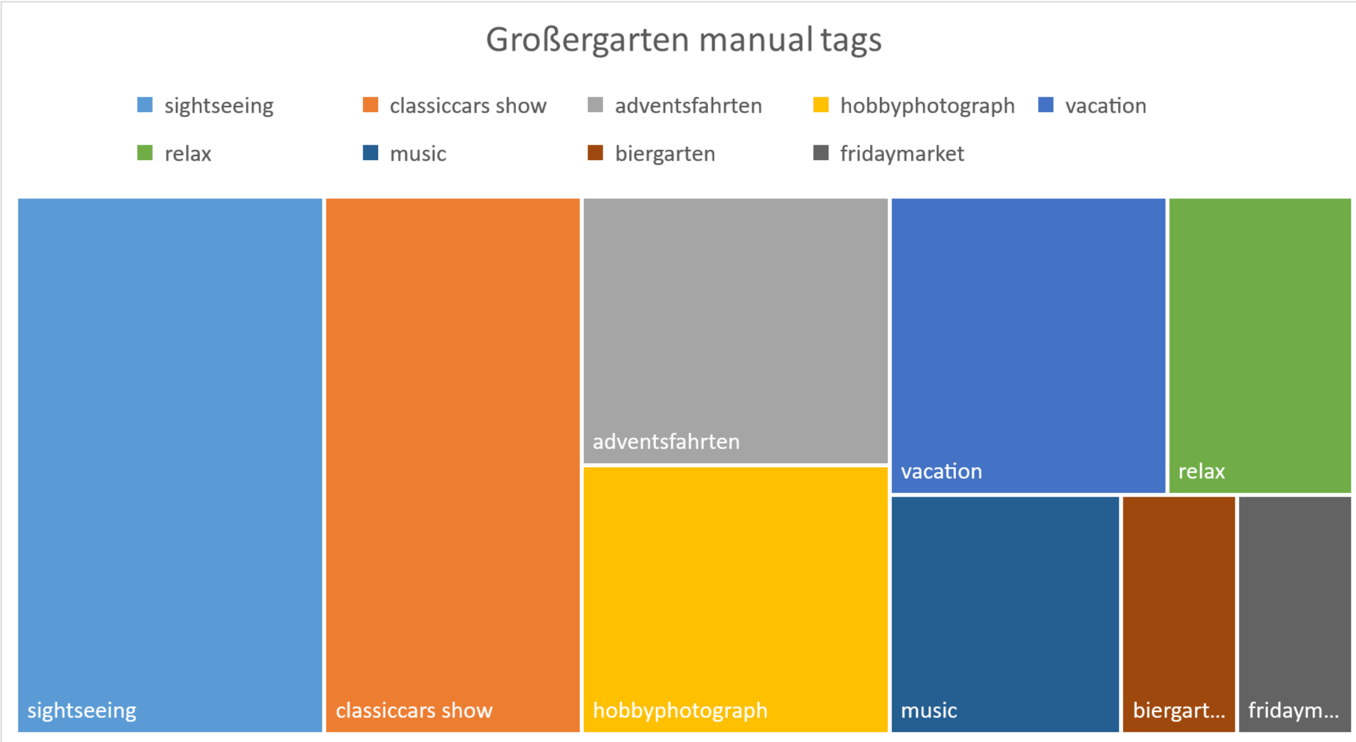


Fig 4.23 Großergarten manual assigned tags

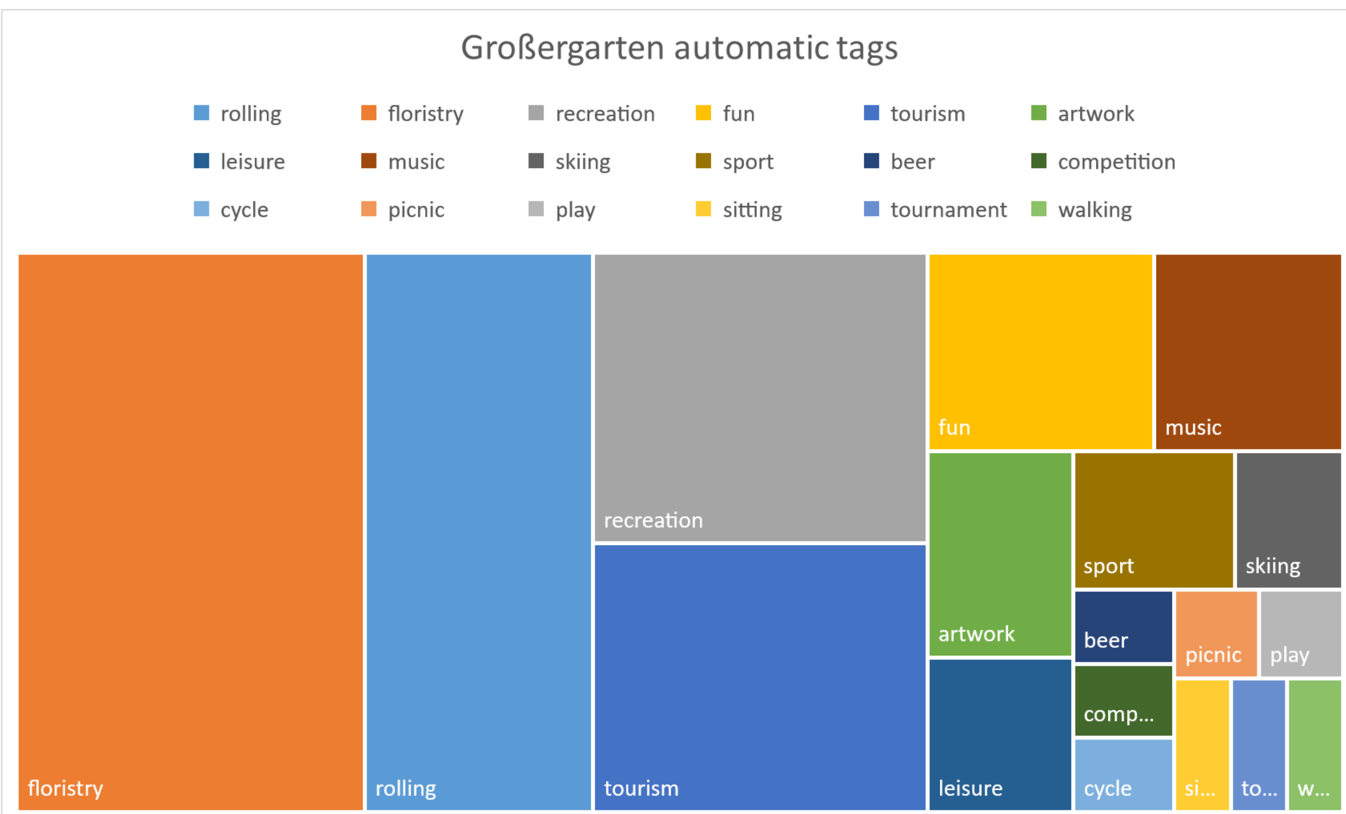


Fig 4.24 Großergarten automatically generated tags

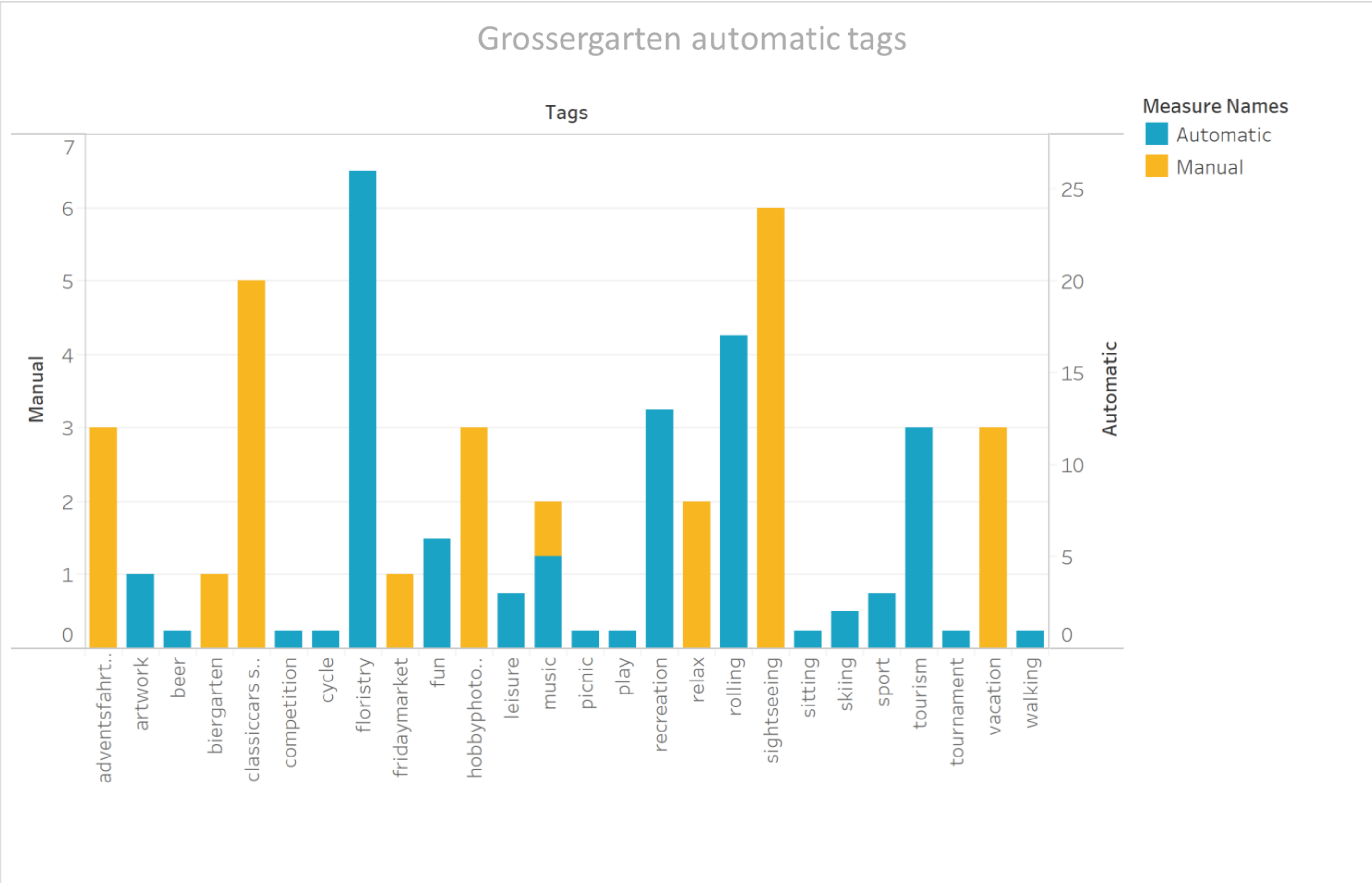


Fig 4.25 Manual & Automatic tags

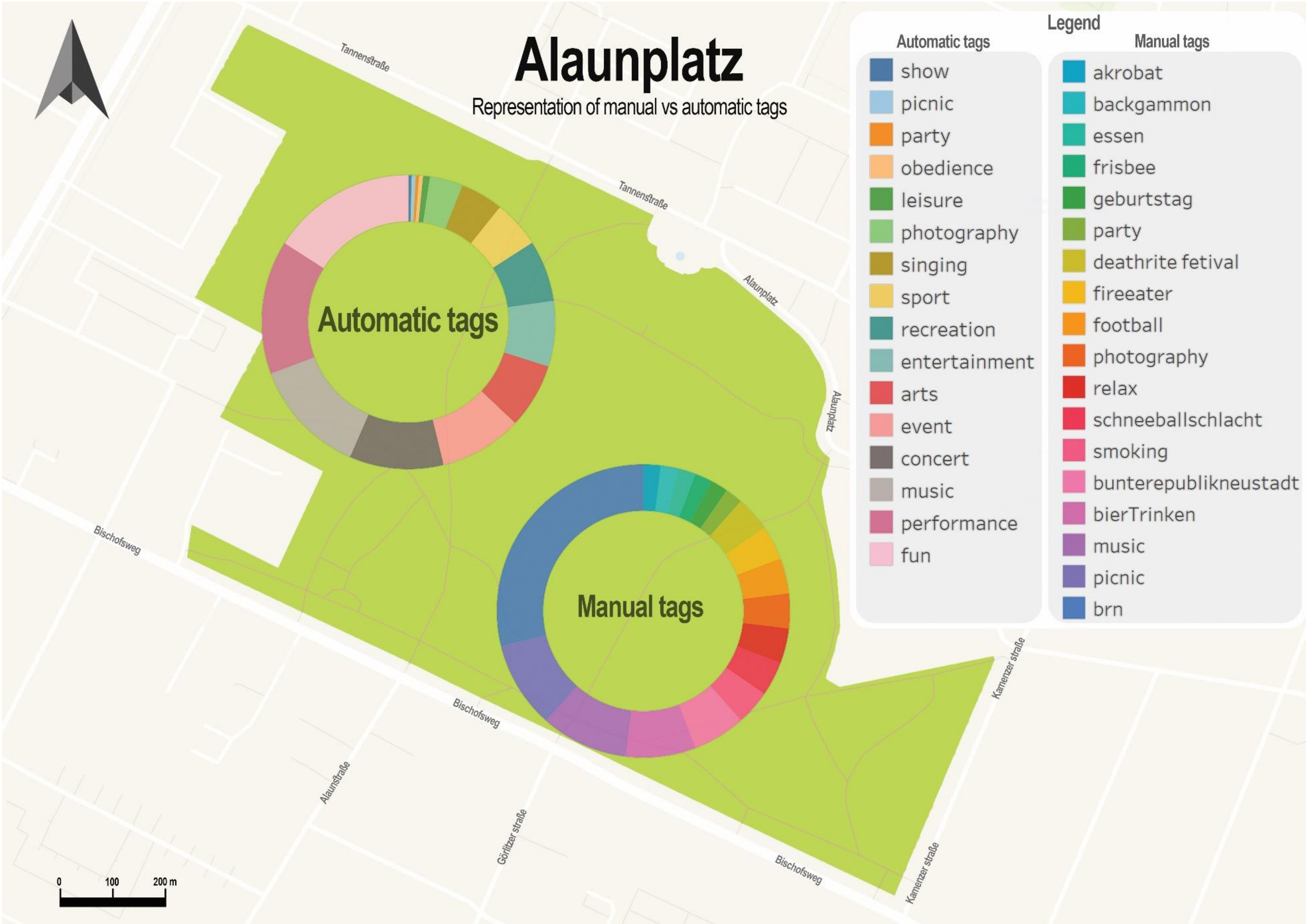


Fig 4.26 Alaunpark comparison

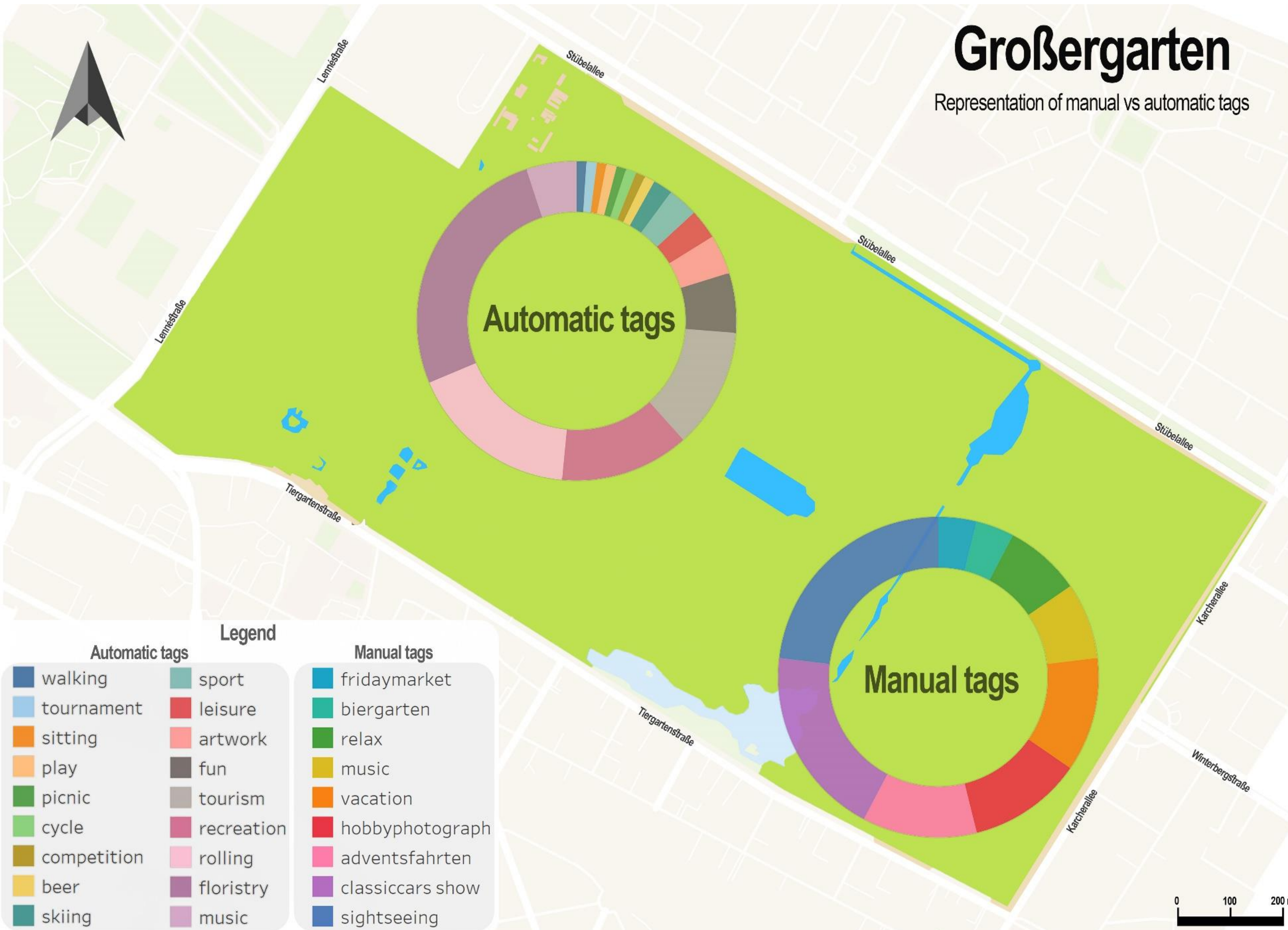


Fig 4.27 Großergarten comparison.

Chapter5: Discussion.

In previous chapters, methodology and results were stated for the comparison of the automatic and manual tagging, Output results were presented from the implementation of study's methodology. In this chapter critical evaluation of the output results and methodology followed is conducted to assess how well the approach answered the research questions. In addition, analysis of results and limitation of research are stated.

5.1 Result analysis

The study confirmed the predictions and the conclusion drawn by Li et al (2004) that image perception differs between computer and humans regarding the recognition and analysis of events or actions inside an image. The examination of images by the system developed in this study resulted in accurate image component description but lacked the cognitive perception (See Fig 4.14, 4.17). As Flickner et al (1995) explain, human image understanding surpasses that of artificial systems and modules, we as humans are better semantic description extractors. Assigning tag word will vary completely from human to machine, humans will attach semantic meaning behind tag words while computers will highlight the extracted feature.

The system was quite accurate in representing the nature of events occurring in the queried images (fig 4.32, fig 4.24) but the overlapping of generated tags with the human assigned ones was not common (fig 4.22, fig 4.25). Humans are often attracted to the most noticeable objects in the scene therefor tagging and representing the image with the most the most relevant words accordingly (Fig 4.16), while the system generates frank descriptions of the image visual elements (Fig 4.6) as found by Gu.et.al (2014).

As an example, a photo was tagged by human with the tag word "Concert" but the tag concert was given the lowest rank by the automatic tagging system, the system gave higher ranks to the frank descriptors tags such as person, musician, and musical instrument. Simply the system's understanding of image purpose is far behind human understanding. (Barnard, et al., 2003) mention that Image annotator tends to ignore the obvious visual aspects of the image and address the very difficult conceived image perspectives, this also explains some reasons for the differences between automatic and manual annotation.

As well as this, human tags tend to represent the name of event or concert or band name they participate in such as “burn fest” or “color fest” but the automatic system just states words as *concert, “event or gathering”* as the cognitive reasoning is not present or very weak.

The results show conformation of predictions regarding the understanding of machines to the human perspective. The majority of manual tags represented experiences and feelings drawn out from the event and the time the photo was taken. As shown in Fig 4.12 and Fig 4.14 the majority of the manual tags represent experience, feelings and conclusions for the experienced moment displayed in photograph (e.g catchy colors) rather than the visual elements.

Further analysis related to the work of (Sen, et al., 2007) shows that every human being differs, they differ in interest , vocabulary, experiences ; therefore the tagging of images tends to be subjective in representing personal human experiences and reflecting different personalities. The tagging system does not reflect past experience in his tag assignment.

Tags might be considered un-reliable as they are totally dependent on the annotator and this makes automatic tagging and annotation challenging, as computers are limited in their knowledge which result in the expression ability. Computer systems lack reflective thinking ability compared to humans, this result in different approach for image analysis therefore different tag annotation.

Since the tag results were ranked by the system ranking of the generated tags was not needed, IR or CBIR evaluation methods were performed on the results to access the accuracy and precision of the system.

According to the study completed by random participants (fig 4.10 and 4.11). the average precision calculated for the system ranged between the values 0.6 and 0.8 with some high and low anomalies, this value indicates that the tagging system was neither very accurate nor in accurate. Overall the system image tagging quality was considered to be above average according to participants.

5.2 Future recommendation.

In order to increase the reliability and accuracy of the comparison and its results, further research should address some limitation of this research. Due to limited time and research scope, certain aspects were taken into consideration while other was not addressed.

As the study's image data was not limited to activity photos and filtration of photos caused some data loss. As result, the photos representing activities or an event were in small numbers compared to the total amount of data. In order to increase the comparison accuracy, more photos representing activity should be assessed. Some parks famous for high rate of different events should be studied further.

As it was out of the research scope to establish ground truth tags for images due to its very high time demand, establishing such data will be of great benefit in assessing the relevancy and accuracy of the computed tags. Ground data would act as a threshold for computed tag compared to and we are able to calculate the recall value and draw PR graph (precision recall graph). As the study focused on assessing Google API for tag generation, using and comparing other systems for tag generation would also be beneficial. Additionally, semantic extraction of the user's flicker tag would assist in a better comparison regarding the quality of tags, as semantic extraction was outside the scope of this research.

Establishing a detailed taxonomy of Flickr tags would assist in overcoming the "Vocabulary Problem" in which different users' uses different terms for describing the same activity (Furnas, et al., 1987).

Chapter 6: Conclusion

This study focused on implementing and using the “Google API” tagging system for automatic tag generation, the output tags are then compared with manual tags. On a more general level the study performed a comparison of automatic versus manual generated tags regarding human activity representation. Flickr images were retrieved and assessed for the areas of Alaunpark and Großergarten, the output is represented as an “Activity tag map”.

For addressing the research questions stated in the first chapter, the study methodology outlined the usage of the Google API system and its setup. While for the comparison step, the methodology included detailed literature review and built upon previous research for the evaluation and analysis of results.

Analysis of results showed how automatic tags compare to manual, also how well they represent the human activity, this gives an idea how close machine and human understanding is. The work presented an assessment for the outputs as comparison. This assessment revealed an above average relation between automatic and manual tags but with perspective differences, while the results did not match 100%, further advancement in the field of AI and machine learning will provide a great push for accurate image analysis.

The automatic tags were a good image descriptors but lacked the reasoning and perspective that of humans. As our survey showed that automatic tags were relatable to images according to a neutral point view.

While certain limitation apply, further research can be built upon this research to increase the accuracy of results by adopting other comparison methods and addressing the challenges faced during the study. This research gives the tools and the means for further detailed analysis. Certain issues regarding the image copyrights and ethical standards should be addressed for privacy protection of people.

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Appendices

Appendix A

Tagging system “Google API”

```
set GOOGLE_APPLICATION_CREDENTIALS=apikey.json
```

```
import io
import os
import glob
from google.cloud import vision
from google.cloud.vision import types
client = vision.ImageAnnotatorClient()

for file_name in glob.iglob('images/*.jpg'):
    # file_name = os.path.join(
    #     os.path.dirname(__file__),
    #     'football.jpg')

    with io.open(file_name,'rb') as image_file:
            content = image_file.read()

    image = types.Image(content=content)

    response = client.label_detection(image=image)

    labels = response.label_annotations
    print("labels:")
    f = open("result.txt", "a")
    f.write("Label Description                Label score ")
    for label in labels:
        print (label.description, label.score)
        f.write(label.description)
        f.write("  ")
```

```
        f.write(str(label.score))
        f.write("\n")
```

Image selection

```
import os


# Open the file with read only permit
f = open('DresdenPart1(Alaun).csv')
# use readline() to read the first line
line = f.readline()
# use the read line to read further.
# If the file is not empty keep reading one line
# at a time, till the file is empty
list_of_names = []
while line:
    if "alaun" in line:
        m = line.split(',')
        list_of_names.append(m[0])
        line = f.readline()
    else:
        line = f.readline()
f.close()



cwd = os.getcwd() # get the current working directory
for image_name in list_of_names:
    previous_location = cwd + "/" + image_name
    #print image_name
    new_location = cwd + "/new/" + image_name
    try:
        os.rename(previous_location,  new_location)
    except:
        pass
```

Image selection without keyword

```
import os

# Open the file with read only permit
f = open('DresdenPart1(Alaun).csv')
# use readline() to read the first line
line = f.readline()
# use the read line to read further.
# If the file is not empty keep reading one line
# at a time, till the file is empty
list_of_names = []
while line:
    m = line.split(',')
    list_of_names.append(m[0])
    line = f.readline()
f.close()
cwd = os.getcwd() # get the current working directory

for image_name in list_of_names:
    previous_location = cwd + "/" + image_name
    #print image_name
    new_location = cwd + "/new_no_alaun/" + image_name
    try:
        os.rename(previous_location,  new_location)
    except:
        pass
```

Word count

```
import os


# Open the file with read only permit
f = open('GrosserGartenCompleteFIlerupdated.txt')  File name
words_dict = {}
line = f.readline()
while line:
    for word in line.split():
        # to remove the result for the numbers and the empty dashed line and
the image name
        if ((not ("0" in word ) )and (not ("-" in word ) )  and (not (".jpg"
in word ) ) ) :
            words_dict[word] = words_dict.get(word,0) + 1
    line = f.readline()
f.close()
file_to_write = open('result_word_count.txt', 'w+')
for key in sorted(words_dict):
    print("{} : {}".format(key,words_dict[key]))
    file_to_write.write("{} : {}".format(key,words_dict[key]))
    file_to_write.write("\n")
```

Library matching

```
f1 = open("Tags.txt", 'r')
f2 = open("Activity library.txt", 'r')
words1 = f1.read().split()
words2 = f2.read().split()
words = set(words1) & set(words2)
with open('filteredTags.txt', 'w') as output:
    for word in words:
        output.write('{} appears {} times in f1 and {} times in
f2.\n'.format(word, words1.count(word), words2.count(word)))
```

Appendix B

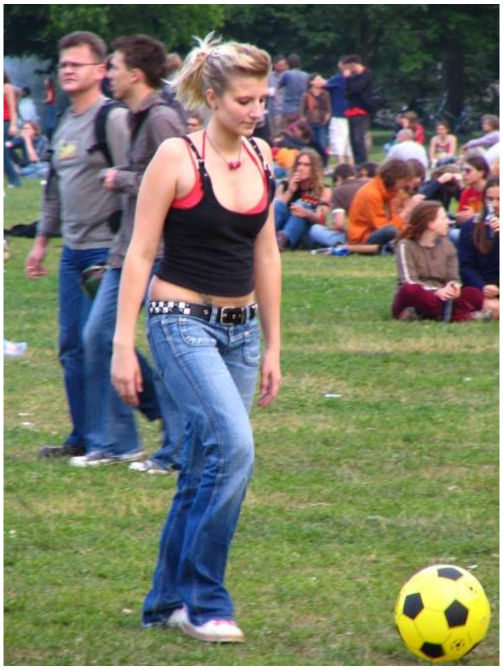
Survey

Please Check which tags are (Relevant, Non-relevant, unsure If you cannot decide) of the images below.

Q1

	Relevant	Non-relevant	Unsure
Woman	X		
mammal		X	
vertebrate		X	
fun	X		
girl	X		
grass	X		
plant		X	
public event	X		
recreation	X		
summer	X		

Q2



	Relevant	Non-relevant	Unsure
Mammal		X	
Grass	X		
Vertebrate		X	
Lawn	X		
play		X	
fun	X		
outdoor recreation	X		
recreation	X		
summer	X		

Q3

	Relevant	Non-relevant	Unsure
saxophone	X		
music	X		
woodwind instrument		X	
wind instrument			X
musician	X		
baritone saxophone			X
musical instrument	X		
brass instrument			X
saxophonist 0.68383461237	X		
jazz 0.630218207836	X		

Q4

	Relevant	Non-relevant	Unsure
mammal			X
vertebrate			X
dog	X		
conformation show		X	
dog like mammal			X
obedience trial		X	
grass	X		
dog breed group			X
animal sports			X
recreation	X		

Q5

	Relevant	Non-relevant	Unsure
plant		X	
tree		X	
grass	X		
vertebrate		X	
day	X		
woody plant		X	
public space	X		
outdoor recreation	X		
vehicle		X	
lawn	X		

Q6

	Relevant	Non-relevant	Unsure
heat	X		
fire	X		
flame	X		
performance art	X		
fun	X		
performing arts	X		
darkness	X		
event	X		
night	X		
performance	X		

Q7

	Relevant	Non-relevant	Unsure
Plant		X	
grass		X	
fun	X		
outdoor recreation	X		
sports	X		
recreation	X		
tree		X	
lawn	X		
leisure	X		
summer	X		

Q8

	Relevant	Non-relevant	Unsure
people	X		
crowd	X		
plant	X		
mammal		X	
man		X	
vertebrate		X	
day	X		
grass	X		
outdoor recreation	X		
male		X	

Q9

	Relevant	Non-relevant	Unsure
snow	X		
footwear		X	
winter	X		
freezing	X		
ice	X		
tree		X	
winter sport	X		
fun	X		
ice rink		X	
ice skate		X	

Q10

	Relevant	Non-relevant	Unsure
plant		X	
green	X		
nature	X		
lawn	X		
grass	X		
mammal		X	
tree	X		
vertebrate		X	
woody plant		X	
fun	X		

Q11

	Relevant	Non-relevant	Unsure
plant	X		
tree	X		
red	X		
leaf	X		
nature	X		
woody plant	X		
flower			X
pink			X
branch	X		
flora			X

Q12

	Relevant	Non-relevant	Unsure
people	X		
plant		X	
grass	X		
tree	X		
outdoor recreation		X	
lawn	X		
leaf	X		
leisure	X		
recreation	X		
picnic	X		

Q13

	Relevant	Non-relevant	Unsure
winter	X		
snow	X		
tree	X		
path	X		
freezing	X		
woody	X		
sky	X		
cross country skiing	X		
winter sport	X		
nordic skiing	X		

Q14

	Relevant	Non-relevant	Unsure
transport	X		
rail transport	X		
train	X		
locomotive	X		
track	X		
rolling stock		X	
vehicle		X	
railroad car		X	
tree		X	
plant		X	

Q15

	Relevant	Non-relevant	Unsure
recreation			X
building			X

Q16

	Relevant	Non-relevant	Unsure
night	X		
light	X		
lighting			X
evening	X		
city	X		
restaurant			X
function hall			X
fun			X

Q17

	Relevant	Non-relevant	Unsure
plant	X		
nature	X		
tree	X		
woody plant	X		
grass	X		
road	X		
path	X		
asphalt	X		
recreation	X		
park	X		

Q18

	Relevant	Non-relevant	Unsure
plant	X		
green	X		
mammal		X	
grass	X		
sports	X		
vertebrate		X	
tree	X		
lawn	X		
competition event			X
tournament	X		

Q19

	Relevant	Non-relevant	Unsure
land vehicle		X	
nature	X		
green	X		
tree	X		
plant	X		
grass	X		
leisure	X		
path	X		
cycle sport	X		
vehicle		X	

Q20

	Relevant	Non-relevant	Unsure
transport	X		
motor vehicle			X
train	X		
vehicle	X		
rail transport	X		
rolling stock			X
mode of transport	X		
public transport	X		
track	X		
rapid transit		X	