Automated social media content analysis from urban green areas – Case Helsinki

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1 Introduction

Location-based social media data are increasingly used to understand spatial and temporal patterns of human activities in different environments. Mining of the continuous flow of social media posts has the potential to provide up to date information about where, when and how people use space [3]. Recent advances in the field of computer science such as machine learning enable us to analyze these spatial big data in unprecedented volumes. Here, we discuss the use of location-based social media data together with automated content analysis techniques to support smart spatial planning in cities. In the presentation we focus particularly on urban green areas, using parks of the Helsinki Metropolitan Region in Finland as the study area.

2 Social media data on urban greens

Social media data has been used to study extensively the use of urban areas [13, 1, 10, 5]. In national parks and other recreational sites, social media has been shown to work as a proxy for visitation [16, 15], and as an indicator of people's activities and preferences [7, 8] when compared with official visitor information. In urban green areas, social media has also been used as a proxy for park and trail use with mixed results [4, 6, 17].

3 Need for automated content analysis methods

Various different approached have been used to automatically analyze textual and image content in social media data (Figure 1 and Figure 2), but machine learning techniques are still rarely utilized in addressing environmental questions [3, 2]. Traditional data collection methods such as surveys, activity diaries, GPS tracking to study the use of green areas are costly and usually time consuming to implement, and thus social media analysis has potential to support these efforts. However, most social media content analysis from green areas have been based on manual work, which limits the extent and repeatability of the analysis. Promising examples have shown that automated text content analysis [11] and image content analysis [12] may help filtering content relevant to nature recreation. Also, the combination of different modalities (such as image, text and emojis) can be utilized to enhance the performance of deep-learning algorithms [14], as exemplified in our case study from Helsinki.

4 Platforms vary in their data

Social media platforms differ in popularity and the type of content, and thus the choice of platform(s) may affect greatly the analysis output. Different platforms provide varying

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spatial accuracies for geotagged data: Instagram posts are associated with the predefined Facebook places, Flickr provides GPS coordinates and Twitter a combination of these. Users also post different contents: Instagram is used for sharing momentary experiences, Flickr more professional content on e.g. species and Twitter discussions on topical issues. Urban social media studies are often based on Twitter or Foursquare, whereas environmental studies have used most widely Flickr and Panoramio. Users also share content across platforms. For example, a geotagged tweet might actually be an Instagram posts (in a sample dataset from Helsinki, over 50 % of the geotagged tweets originated from Instagram). The way in which users communicate in each platform (using text, emojis, image and video) should be taken into account when designing and training classifiers [9].

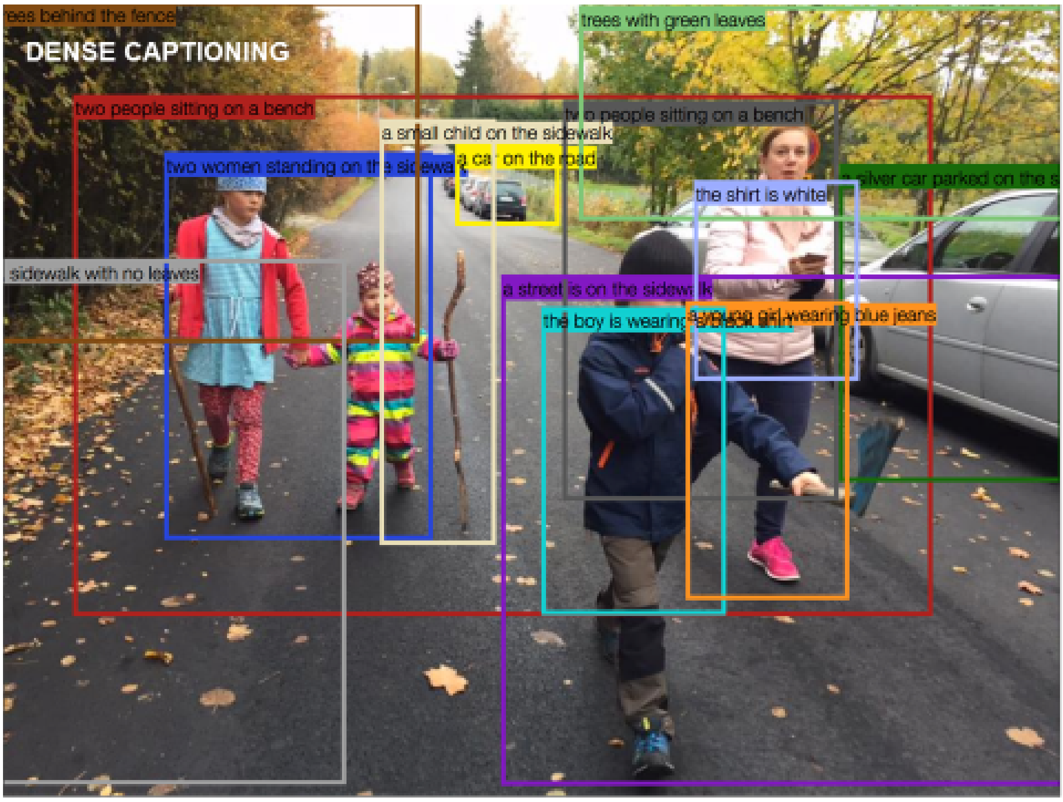

Figure 1 Dense captioning allows verbalizing image content to natural language that can be analyzed more easily.

5 Multimodal analysis (text + image) brings added value when detecting activities

Our dataset from Helsinki contained 11 000 geotagged Instagram photos located within regionally important green areas (all available data from 2015). The dataset was manually annotated for the presence and absence of human activities (24 % of the data contained an activity), and split to training, validation and testing samples for the automatic activity detection. Automatic activity detection was done separately for images and captions (monomodal classification), and trough fusion of features extracted from images and captions (multimodal classification). Images were analyzed using NasNet-L pre-trained on ImageNet,

Figure 2 Identifying objects and people allow further analyses of what people have been imaging (an example using MASK R-CNN)

and Captions were analyzed using fastText word embeddings trained on all available captions. Our preliminary analysis shows that multimodal methods are most effective in identifying activities automatically: automated detection of activities from the posts was most successful when combining both the textual and image content. With text only, we reached F1 score of 0.71, with image only 0.76 and with their combination 0.84 [9].

Future work will include the comparison of content from different platforms, and further analysis of the spatial activity patterns in urban green areas.

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