

INTERACTIVE MEDIATISED URBANISM

Shaping High Emotional Value Food Consumption Spaces with Human Data on Social Media

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Abstract. Research in the field of shaping urban spaces with emotional values on social media is still lacking. This paper attempts to shape an urban food consumption space with high emotional value through digital interactive media consisting of machine learning and other algorithmic processing of the emotional values contained in images of urban food consumption venues posted by humans on social media for the food consumption process. Images on social media that contain geographic information on the food market with research conditions are used as the data source, which is filtered by algorithms for the emotional value data. The filtered images are put into a machine learning model for training, resulting in a series of spatial images containing high emotional values, which are used as learning objects for the pictures entered by the user community at the input side of the system. The depth information in the output objects is read to transform them into spatial models, and the information from these virtual spatial models that have been learned for higher emotional values is the output of user interactions and the basis for improving the food consumption space.

Keywords. Social Media Database, Human-Urban Interactive Media, Computer Visualization, Image-to-Model, Food Consumption space, Emotional Values, Machine Learning, AR Interface

1. Introduction

Research into the analysis of data from user communities on social media has general applicability across a variety of fields, facilitated by the quantity and diversity of user data on social media platforms and the ease of access to open source. As noted by Zachlod et al. in their study of social media in 2017, social media-based research is constantly expanding. (Zachlod et al,2017) In urban design as well as architecture, there is also a significant amount of research on various branches of the field using data from user communities on social media as a database. In ‘Experiencing Urban Spaces and Social Meanings through Social Media’ (Gatti and Procentese,2021), the authors study the mapping of interpersonal relationships in urban spaces through the emotions

of posts on social media. Compared to this, the current stage of scholars' research on social media data in urban design also focuses on the influence of urban space on human behaviour. However, there is still a lack of research on the impact of urban space on human behaviour in specific human behaviours, and how human feedback emotions can further shape urban space.

According to the State of Food and Nutrition Security in the World (SOFI), about 2 billion people do not have access to safe and nutritious food, and even in urban areas with high levels of consumption, the experience of food consumption varies due to spatial constraints and poor information. (Ruel, 2020) Therefore, there is a need to revisit the process of food consumption from an urban perspective.

Currently, some food market operators adjust food types or consumption space based on user community feedback, such as Granville Island Public Market in Vancouver, which has expanded its range of artisanal products based on user preferences, or Borough Market in London, which adjusts the number and location of cafés in its moveable shops based on changes in the number of commuters on weekdays and weekends. This kind of evaluation of social media data rationalises and improves the consumer's food consumption experience. However, how social media data is used in this process still warrants further research, such as the human subjectivity of the data analysis and the fact that it is not from the perspective of the user community. It is worthwhile to investigate systems with unconscious-based machine learning algorithms that enable users to engage in active interactions if the system can help humans create space with high emotional value. The paper will investigate this hypothesis and compare it with the discussion.

2. Methodology

2.1. EMOTIONAL VALUES IN SOCIAL MEDIA

2.1.1. Datasources

In an interview with Darren Henaghan, it was stated that Borough Market, a food market, has a footfall of 15.5 million people per year, and even up to 100,000 people per day during the holiday season. With the correlation between footfall and data posted by people on social media, the market has a sufficient amount of data that is very favourable for studying the food consumption process. Therefore, the research of this paper will be based on social media user data from the Borough Market area. In terms of the choice of social media platforms, the study 'Revealing Cultural Ecosystem Services through Instagram Images' points to the importance of geographically informative images for the study of urban space (Guerrero et al, 2016).

However, although the information on Twitter, which has the largest user community, can be crawled through APIs, most of it does not have latitude and longitude geographic information. As Kalev Leetaru et al pointed out in 2013, only one-third of the posts can be located by GPS when studying user data on the Twitter platform. Based on the reliability of the Flickr platform for crawling geographically informative images as argued in Extracting and understanding urban areas of interest using geotagged photos, I chose this platform as a database source. I chose this platform

as the database source. In this study, I used the API to crawl 62,290 posts (1,510 images were filtered) on Flickr from the period of 2021-2022 by users around the area of Borough Market as the input database.

2.1.2. Emotional Values of Images with Spatial Data

By using the Flickr plugin in QGIS, geographically detailed SHP files with these images can be obtained and rendered in GIS, it can be observed that the number of images posted varies from region to region. By using NLTK (A leading platform for building Python programs to work with human language data) in Python and TextBlob Library to analyse the text of Flickr posts, the captured data is classified in terms of emotional value and the results are presented through Grasshopper. Warm areas are areas with more posts of high sentiment value, and cold areas are of lower sentiment value, and it can be roughly judged that the sentiment values of different areas of the food market are statistically different in big data. However, these data contain a lot of spatially irrelevant images and text, which need to be filtered by algorithms.

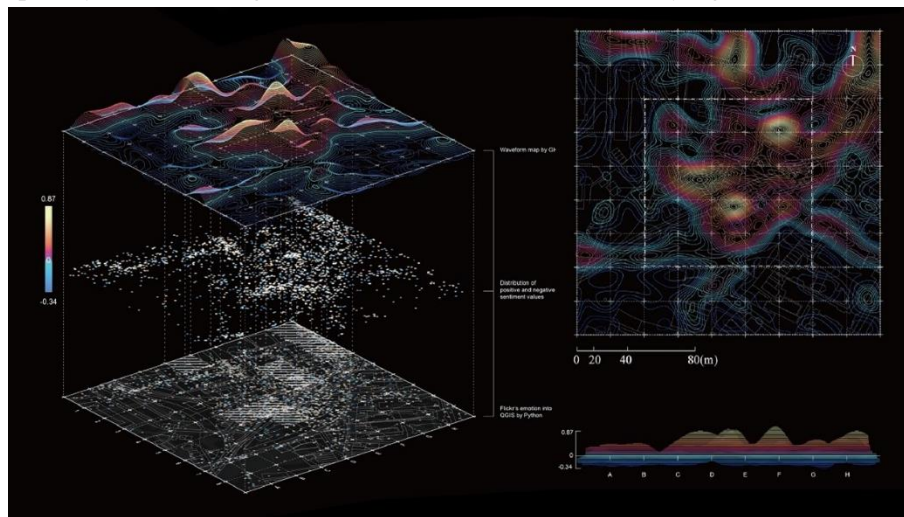


Figure 1. An Emotional Map based on the data from GIS

Therefore, it is necessary to filter the images in the dataset to filter out the images that do not contain urban space. In the field of visual emotion, there have been a large number of researches by scholars, such as Convolutional Neural Network CNN. This study invokes Deepsentibank, a deep learning framework based on caffe maintained by the Berkeley Visual Learning Center (BVLC) and community contributors, which uses a CNN architecture with 8 major layers with weights, trained on about 826,806 images on Flickr, and mainly works to extract the noun (object recognition) and

adjective (sentiment analysis) information in the images. (Chen et al, 2014)

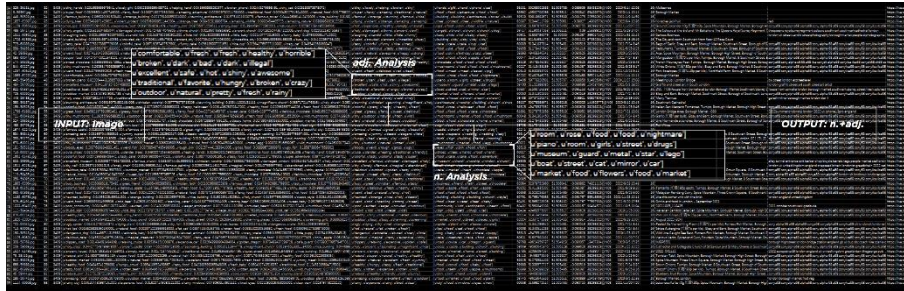


Figure 2. Deepsentibank is a tool to pick up adj. and n.

Through Deepsentibank's recognition of nouns in images, the input image pool is categorized, and the images that are recognized as having a higher proportion of architecture will be used as the object of subsequent research.

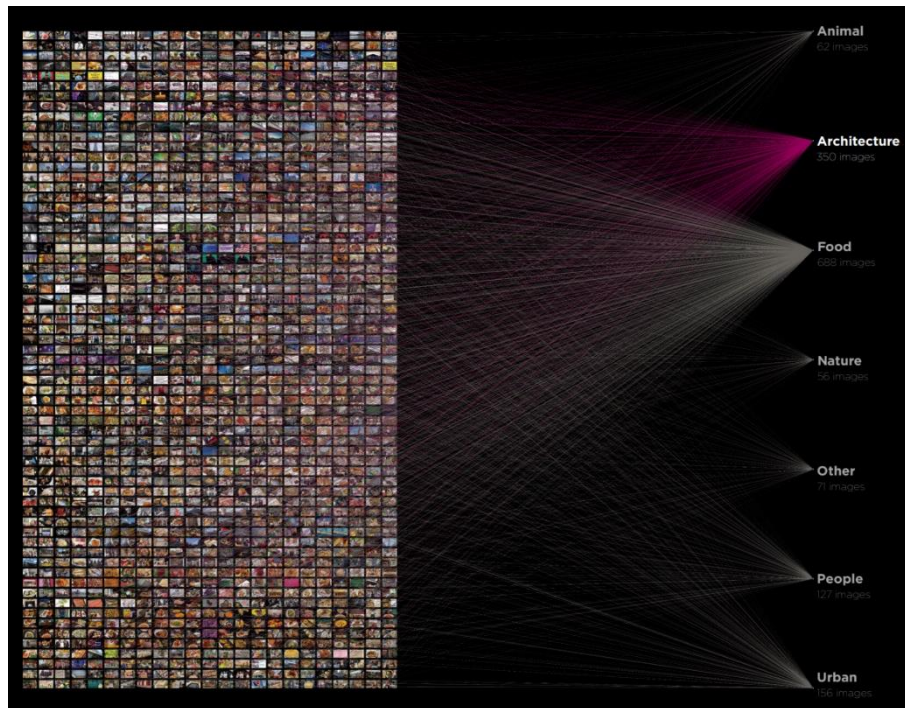


Figure 3. Filtering image content

Using the second step of this algorithm, the adjectives contained in each image identified as having a high likelihood of architecture content are extracted using Deepsentibank. These adjectives can be divided into a four-quadrant coordinate system based on the theory of Interpersonal Circumplex proposed by James Russell in 1980,

which classifies adjectives that contain human emotions. Surprise, happiness, sadness, and calm are the four axes respectively. (Russell, 1980) For example, words located in the first quadrant between surprise and happiness have the characteristics of positive affect + high motivation, according to the coordinates of different adjectives, the tendency of the adjective can be observed, which is plotted in a table from -2 to 2.

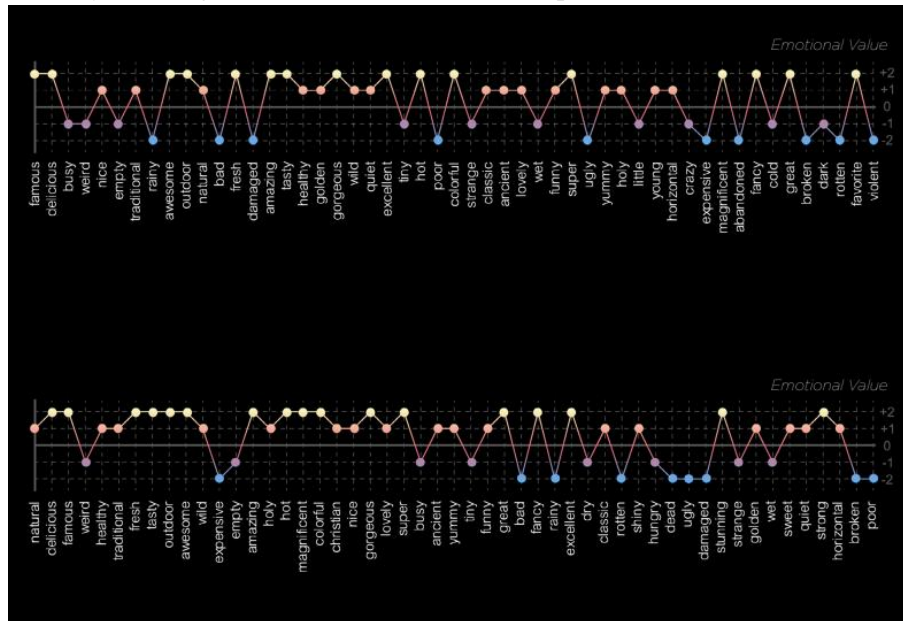


Figure 4. Sentiment values of different words contained in different images

Thus, the images with spatial information in the images uploaded by users on the social media Flickr, and the coordinates of the emotional values corresponding to each of them were obtained. After obtaining these reference objects that are judged to be of high emotional value, how to go about realizing the emotional values contained in these images is the next step that needs to be done.

2.2. EMOTIONAL VALUES TRANSFER TO SPATIAL INFORMATION

2.2.1. High Emotional Value Images Training Model

These images judged to be of high emotional value are fused using stable diffusion: using two Images overlay, continuously inputting images and overlaying them with the first two images, which will eventually be iterated into images with a certain characterization based on all the input images. The image generated by 'Borough Market Training Model' is used as the input for the next step.

2.2.2. Image transfer to model

To analyze the spatial information in these filtered images containing information about urban architecture, it is necessary to identify the three-dimensional spatial

information that has been projected onto the two-dimensional image. The determination of perspective angles and the capture of spatial elements in the images requires the use of algorithms to accomplish this accurately and in batches. This is different from taking multiple photos and compositing them into a 3D model, such as recap from Autodesk and object capture from Apple, where people on social media take photos for the purpose of sharing, entertainment, etc., rather than professionally scanning an area, such as in the pre-survey of a site for an architectural design. This kind of spatial recognition based on a single photo with perspective from a human's point of view needs to be built on a large amount of training. Algorithms based on Convolutional Neural Networks (CNNs) are commonly used, and their workings are described in detail in the May 2020 publication 'Architecture of Convolutional Neural Networks (CNNs) demystified'. The model with this specified training method is called 'Single image depth estimation' (Mertan et al, 2021).

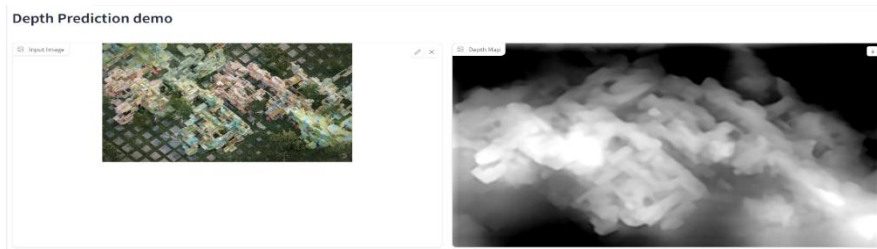


Figure 5. 2D image's depth information

After comparing the existing several latest Single image depth estimation conversion methods, such as Ground-truth Depth, DTS-Depth, Predicted Depth, BTS, Chen et al, Fast Dept, etc., it is not difficult to find that different machine learning algorithms have different responses and recognition accuracies for different spaces on the data output, the response speed and recognition accuracy for different spaces have variability, and there are also differences in data presentation. Finally, I chose Zoe Depth, which was recently published in February this year. (Bhat et al, 2023)

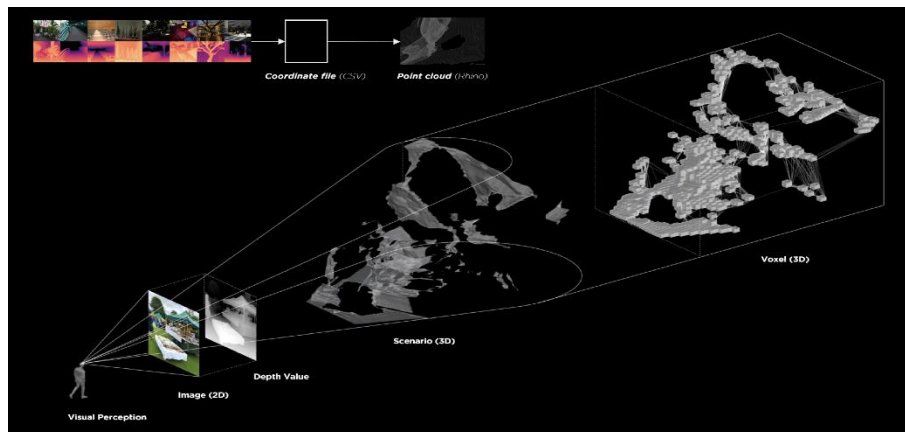


Figure 6. 2D Image transfer to 3D model

Putting any spatial image into the input side of Zoe Depth results in a Depth Value map and a preliminary 3D model. Using a plugin such as Grasshopper's Mesh-edit, the output Scenario3D model can be plotted to obtain a Point Cloud.

2.3. EMOTIONS-SPACE INTERACTIVE MEDIA

The high emotional value of the space produced by the training model generated by the computation and reading of the images used on social media in the Borough Market area is a reference system. Whenever a user arrives at the mall and takes a picture and uploads it to the interactive media system, it is overlaid with the high emotional value images and a new Voxel Model is generated that has some correlation with the high emotional value.

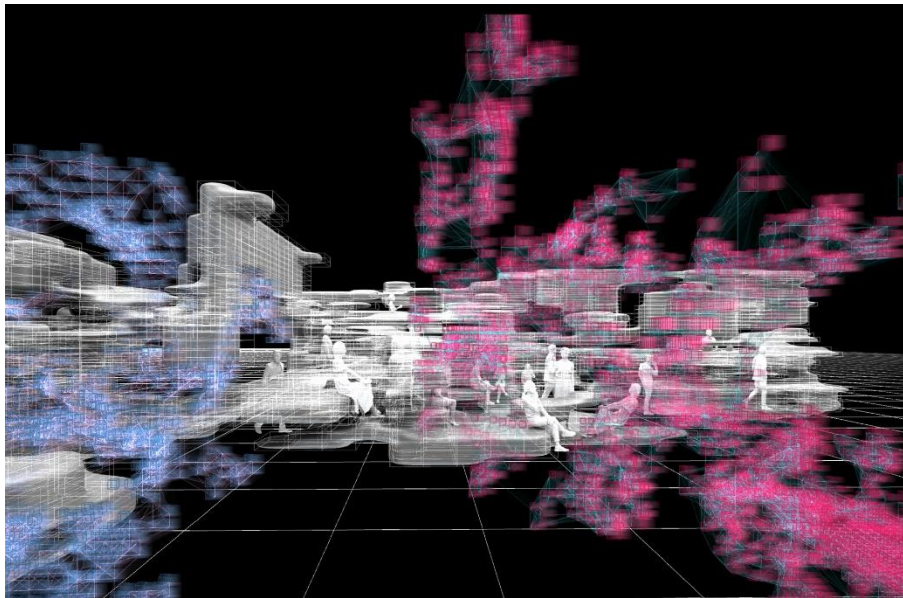


Figure 7. Voxel overlay

These voxel models will be constantly superimposed in the virtual venue, which can be seen first through the AR program in the system I built. For merchants, the locations of voxels uploaded by users can be used to determine which types of food and which food outlets are more popular. For users, they can see the locations of outlets that are of interest to other users and that can generate pleasurable emotions. More importantly, at the level of human interaction with urban space, the voxel will gradually take the shape of an architectural space with more iterations, which can serve as a prototype of a food consumption space generated by human emotions.



Figure 8. AR interface

These prototypes can be constructed using some of the waste products of the food consumption process, such as plastics and fabrics, and ultimately become part of shaping the reality of urban food consumption spaces.

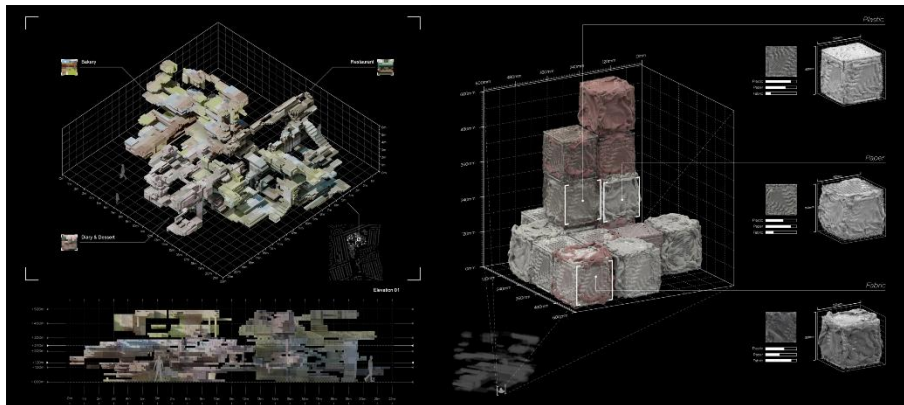


Figure 9. Built based on prototypes

3. Results

Through the collection of human emotional data on social media, a digital system formed with machine learning tools such as Deepsentibank, stable diffusion, and Zoe-Depth is able to serve user groups to interact spontaneously. By taking pictures of the place during food consumption and the feedback of their emotional values, users influence other humans who are in the place (other users and market operators) and thus reshape the place of food consumption urban space. The Voxel model of the virtual interface is traced back to the emotions of each participating user before iterating through unconscious algorithms, which is the biggest difference from other studies that collect data on social media.

4. Discussion

This experiment is prospective for shaping urban space through human emotions, but there are still some shortcomings. The first is three points about the data sources for the experiment. When collecting posts from humans on social media, there is no way to count all users on all platforms, and the data itself is incomplete. At the same time, the data was sampled from Flickr, which is not the largest social media site, so the data has limitations. Using the API also has time period limitations for getting the data. Second, when filtering data, such as using Deepsentibank, this kind of big data model formed after image training, there are inherent errors, and its judgment of the content of the image and the emotional value contained in it is not completely accurate. In the process of data training, there is also uncontrollability, the error of stable diffusion is similar to that of Deepsentibank, but due to the fact that the number of screened images with high sentiment and including spatial information of buildings is not large, the error of 'Borough Market Training Model' error will be larger. In the transformation of the data, the 2D image to 3D model technology on which Single Image Depth Estimation is based is not mature enough, and the restored space is not accurate.

These are the limitations of the generation algorithm in this interactive media, and also the limitations of the users accessing this interactive media, not all of them are willing to use the AR app, and not all of them are willing to take photos and upload them in the system, so the final iteration of the system generates an inaccurate prototype of the food consumption space. These prototypes, if not actually constructed, are missing a large part of the significance of shaping the actual urban space. However, this exploration of creating new interactive media through the research of human emotional values and translating them into specific spaces is still valuable to the field.

5. Conclusion

This research aims to fill the gap in the application of social media in the field of urban design and proposes an innovative media interaction system by exploring how to transform human emotional data on social media into spatial prototypes of food consumption in three-dimensional space. The spatialized expression of emotional data is realized by analyzing and filtering spaces of high emotional value and applying them to the interactive experience of human beings in the process of food consumption. This study not only demonstrates the potential value of social media data in urban space design, but also provides new perspectives and practices on how to better combine human emotional data with urban space design in the future, providing methodological guidance in this field.

References

- Bhat, S. F., Birkl, R., Wofk, D., Wonka, P., & Müller, M. (2023). ZoeDepth: Zero-shot Transfer by Combining Relative and Metric Depth.
- Chen, T., Borth, D., Darrell, T., & Chang, S. F. (2014). DeepSentiBank: Visual Sentiment Concept Classification with Deep Convolutional Neural Networks.
- Gatti, F., & Procentese, F. (2021). Experiencing urban spaces and social meanings through social Media: Unravelling the relationships between Instagram city-related use, Sense of Place, and Sense of Community. *Journal of Environmental Psychology*, 78.

- Guerrero, P., Møller, M. S., Olafsson, A. S., & Snizek, B. (2016). Revealing Cultural Ecosystem Services through Instagram Images: The Potential of Social Media Volunteered Geographic Information for Urban Green Infrastructure Planning and Governance.
- Leetaru, K., Wang, S., Cao, G., Padmanabhan, A., & Shook, E. (2013). Mapping the global Twitter heartbeat: The geography of Twitter. *First Monday*, 18(5).
- Mertan, A., Duff, D. J., & Unal, G. (2021). Single Image Depth Estimation: An Overview.
- Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, 39(6), 1161-1178
- Zachlod, C., Samuel, O., Ochsner, A., & Werthmüller, S. (2022). Analytics of social media data – State of characteristics and application. *Journal of Business Research*, 144, 1064-1076.