Using Spatial Analysis, determine if Emotional Geography exists in Crowd Behavior in Public Spaces

Advanced Spatial Analytics Spring 2019

Project 2

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Approximately 4,500 words

1. Introduction

The objective of this paper is to investigate if there is an Emotional Geography to crowd behavior in public spaces.

2. Literature Review: Emotional Geography

Emotional Geography is a relatively unexplored field, having only developed recently after Geography took an 'emotional turn'. There has yet to be a universal agreement on the definition of Emotional Geography, but we understand that Emotional Geography deals with the relationships between human emotions and physical surroundings.

In *Emotional Geographies (2007)*, Davidson, Bondi, and Smith defined Emotional Geography to be an "[attempt] to understand emotion – experientially and conceptually – in terms of its socio-spatial mediation and articulation rather than as entirely interiorised subjective mental states"[1]. In a seminal paper by Anderson & Smith in 2001[2], the duo contends that emotions are crucial in the pursuit of understanding the interconnected yet unequal world, to the extent that "neglecting the emotions leaves a gaping void in how to both know, and intervene in, the world." They advocated for an awareness of how emotional relations shape society and space, which in return "sparked a response from various geographers describing a range of emotions in various contexts including ambivalence, anger, awe, betrayal..., embarrassment, fear..., happiness and pain"[3].

Specifically, Barsade (2015)[4] as well as Hatfield (1955)[5] promulgated the idea of group emotional contagion, where the sharing of emotions exist. Bartel and Saavedra (2000) [6] also found evidence of mood convergence in group settings.

The relationship between the existence of emotions and geography have become more apparent over the years, and based upon prior literature, the team has sought to investigate if emotional geography exists, and in particular in relation to crowd behavior in public spaces in New York City.

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[1] "Emotional Geographies - Google Books." https://books.google.com/books/about/Emotional_Geographies.html?id=F6xL344M0IMC. Accessed 28 Apr. 2019.

[2] (n.d.). Editorial: Emotional Geographies - University of Western Sydney. Retrieved April 22, 2019, from http://www.uws.edu.au/__data/assets/pdf_file/0008/150947/Anderson_and_Smith_EmotionalGeographies_ICS_Pre-Print_Final.pdf

[3] (2009, December 9). Emotions and affect in recent human geography - Pile - 2010 .... Retrieved April 22, 2019, from https://rgs-ibg.onlinelibrary.wiley.com/doi/10.1111/j.1475-5661.2009.00368.x

[4] (n.d.). The Ripple Effect: Emotional Contagion and its ... - SAGE Journals. Retrieved April 29, 2019, from https://journals.sagepub.com/doi/abs/10.2307/3094912

[5] (n.d.). Emotional Contagion - Jstor. Retrieved April 29, 2019, from https://www.jstor.org/stable/20182211

[6] (n.d.). The Collective Construction of Work Group Moods - MIT. Retrieved April 29, 2019, from http://web.mit.edu/curhan/www/docs/Articles/15341_Readings/Affect/Bartel.pdf

3. Project Methodology

Data was mainly taken via two approaches: web scraping as well as first hand primary fieldwork.

3.1. Initial Assessment

The team first sought to get a broad overview and a sense of emotions across New York City. To do this, we decided to use online data from Flickr, an image hosting service website, and from Twitter, a platform where users can post 'tweets' which are essentially short posts limited to 280 characters and run the two data sources through open source libraries online to get outputs of emotions. These two platforms were selected because a portion of their data are geotagged, allowing us to extract locations and potentially allowing us to draw a link between emotions and their locations. These two platforms also provided a range of data, collecting emotion and sentiment information from both text and images, allowing a more comprehensive sentiment analysis compared to only using visual or textual features. We were also interested in the comparison between the space geography of emotions exhibited by the two platforms and see if the two exhibit similar relationship between space and emotions.

3.2. Real-Life Observations

In approaching the project, the team referred to Kevin A. Lynch's work on the *'Image of the city'*[7] to determine a starting point from the City to do our observations. Lynch proposed five elements contributing to an image of a city - Paths, Edges, Districts, Nodes, and Landmarks.

The team ultimately decided to collect primary data at landmarks to understand if real-life observations of expressions and emotions are captured in the online sphere. Landmarks are "external defined physical objects such as buildings...frequently used clues of identity...and increasingly relied upon as a journey becomes more and more familiar"[8]. The team believes that Landmarks will have a natural force of attraction thus allowing us to study crowd behavior and then possibly seek out emotions from the crowd. Additionally, it presents a suitable scale for the purpose of this study as Districts and Nodes are too large, and Paths and Edges, too transient.

Our aim is to identify similarities and differences between sentiments collected by the primary data and the sentiments expressed on cyberspace, represented by Twitter and Flickr data. For the purpose of this project, due to time and manpower limitations, the team selected three landmarks to perform data collection.

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[7] (n.d.). The Image of the City | The MIT Press. Retrieved April 28, 2019, from https://mitpress.mit.edu/books/image-city

[8] (n.d.). Kevin Lynch. Retrieved April 22, 2019, from http://www.miguelangelmartinez.net/IMG/pdf/1960_Kevin_Lynch_The_Image_of_The_City_book.pdf

The three sites in New York City were chosen:
1. Entrance of Brooklyn Bridge from Brooklyn,
2. 9/11 Memorial & Museum, and
3. Duffy Square at Times Square.

At each location, we mounted a video camera on a tripod and took 10-minute videos. These videos were then processed before we extrapolated emotions from faces that appeared in the videos for analysis.

3.2.1. Brooklyn Bridge (Entrance from Brooklyn)

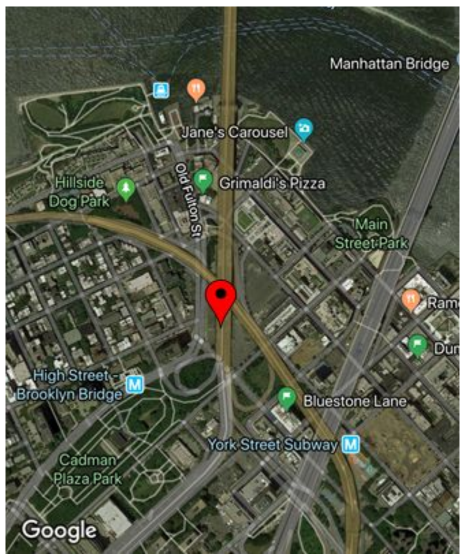

Figure 1. Red pin indicates location of video camera

The Brooklyn Bridge has an average daily usership of 10,000 pedestrians as of 2016[9] and is one of the top tourist attractions in New York City. In 1964, it was designated a National Historic Landmark and National Historic Civil Engineering Landmark in 1972[10]. We selected the Brooklyn side of the bridge and captured video footage of people walking from Manhattan towards Brooklyn (Figure 1).

The Brooklyn Bridge is an interesting study site as it is utilised by a mixture of both tourists and locals (mostly joggers and cyclists) competing for space along a narrow path. Additionally, the start of the Brooklyn Bridge walk from the Brooklyn side doubles as the end of the Brooklyn Bridge walk from the Manhattan side, which may allow us to observe a juxtaposition of emotions between pedestrians with conflicting use of the same space, since they will be moving in different directions and potentially have

[9] "Brooklyn Bridge, the 'Times Square in the Sky,' May Get an Expansion ...." 8 Aug. 2016, https://www.nytimes.com/2016/08/09/nyregion/brooklyn-bridge-expansion.html. Accessed 27 Apr. 2019.
[10] (n.d.). Brooklyn Bridge - Wikipedia. Retrieved April 22, 2019, from https://en.wikipedia.org/wiki/Brooklyn_Bridge

different short-term objectives. The will provide us with a range of emotions detected. For example, it is possible that pedestrians walking from Manhattan are much less excited than the pedestrians who just got onto the bridge from Brooklyn.

3.2.2. Duffy Square at Times Square

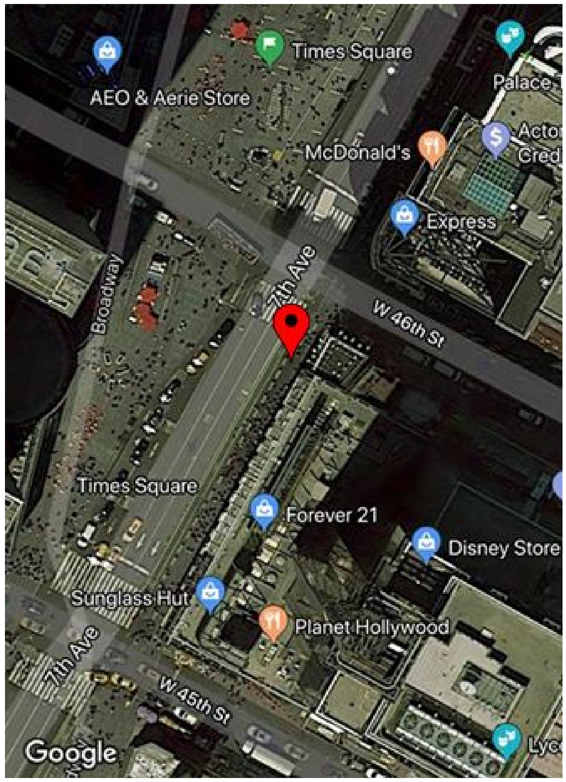

Figure 2. Red pin indicates location of video camera

The giant billboard and flashing neon lights at Times Square is often synonymous with the vibrancy of New York City and represents life in the city. Daily visitorship is estimated to be at 380,000[11] from both tourists and the people that work in the office buildings around Times Square, explaining why the area is teeming with energy. Duffy Square specifically has turned into a landmark location within Times Square because it affords a sweeping view of the whole area from the iconic red steps that provide elevation. Duffy Square is also the perfect location for tourists to take photos as it is surrounded by large iconic LED screens.

The team placed a camera near the intersection of W 46th St and 7th Ave and took a ten-minute video of people walking northwards. We were hoping to capture the expressions of pedestrians while they take in the view of Times Square, possibly allowing

[11] "Pedestrian Counts | Times Square NYC." https://www.timessquarenyc.org/do-business/market-research-data/pedestrian-counts. Accessed 29 Apr. 2019.

us to observe positive emotions. The location was also chosen because it was a relatively narrow path along 7th Avenue, which meant that pedestrian density is higher and more facial expressions can be captured for analysis.

3.2.3. 9/11 Memorial & Museum

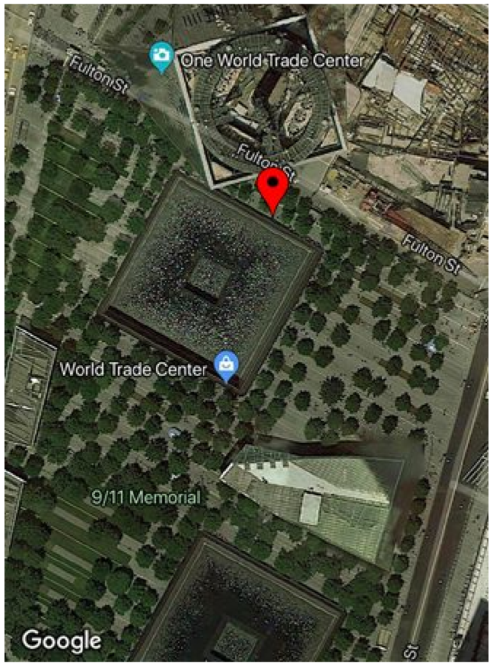

Figure 3. Red pin indicates video camera location

The 9/11 Memorial & Museum is a landmark commemorating the terrorist attack that happened in New York City on September 11 2001. The site is a marker for more than 2600 lives lost and conveys a sombrous and solemn mood. The team thus chose this location to study as we expect to see these emotions mirrored in the expressions of visitors while they mark their respect.

The camera was placed on the path separating the North Pool and the entrance of One World Trade Center, capturing eastbound pedestrians and visitors interacting with the North Pool memorial.

3.3. Cyber Emotions of Landmarks

The team then repeated the initial online sentiment analysis experiment using Twitter and Flickr Sources, but for locations at the three specific landmarks chosen (Brooklyn Bridge, Times Square and 9/11 Memorial). The intention was to examine if there is a discrepancy in emotions demonstrated between the online and actual space.

4. Initial Analysis - Sense of emotions across New York City

4.1. Twitter Dataset

We first utilized the Twitter API to gather tweets from the live stream across New York City. Twitter API allows us to pass location parameters and filter the tweets geographically, so a bounding box of geolocations was passed as a filtering parameter to limit our data collection to the area of New York City. About 60,000 tweets were captured over a period of three days. We stored the data locally and then filtered out the tweets that were geotagged, which returned about 10,000 tweets. Next, we created a geodataframe from the geotagged tweets and performed a spatial join with the Public Use Microdata Area (PUMA) boundaries shapefile. The team decided to use PUMA boundaries because PUMAs are geographical units that the US Census utilise for providing statistical and demographic information, with each PUMA containing at least 100,000 people[12]. Consequently, we were able to create a PUMA-wise dataset of tweets over three days (18th April 2019 to 21st April 2019) for New York City. Here, we note that the dataset of this size might not be representative - data was collected for a short span of time and our analysis might only hold for that period since there can be temporal patterns in the way emotions are exhibited in tweets.

4.1.1. Textual Sentiment Methodology

We used an open source python package Natural Language ToolKit (NLTK) for sentiment analysis of the tweets. The NLTK package is commonly used for text analytics and is specifically capable of analyzing people's sentiments from text sequences in a computationally affordable manner. We chose the NLTK over other Natural Language Processing (NLP) Libraries as it has many third-party extensions and is one of the most established and user-friendly library around. The Sentiment Intensity Analyzer function from NLTK assigns a polarity score to each tweet, ranging from -1 to 1, allocating a score of 1 if the tweet has the most positive sentiment and -1 if the tweet has the most negative sentiment. Finally, we aggregated the sentiment scores across geographical locations in New York City by getting the mean sentiment score, to achieve tweet sentiment scores for each individual PUMA.

Example Tweet	**Sentiment Score**
I love celebrating wins in April and then getting completely shut down by Homer Bailey and the 6-12 KC Royals	0.912
B****** be lying on n***** throwing that abuse word like nothing that's why it takes forever for a women to prove she's been abused	-0.940
Tonight is a two dinners type of night	0.000

[12] (n.d.). Public Use Microdata Areas (PUMA) | NYC Open Data. Retrieved April 27, 2019, from https://data.cityofnewyork.us/Housing-Development/Public-Use-Microdata-Areas-PUMA-/cwiz-gcty

Table 1. Examples of Tweets and corresponding Sentiment Scores, censored for expletives

4.1.2. Textual Sentiment Analysis

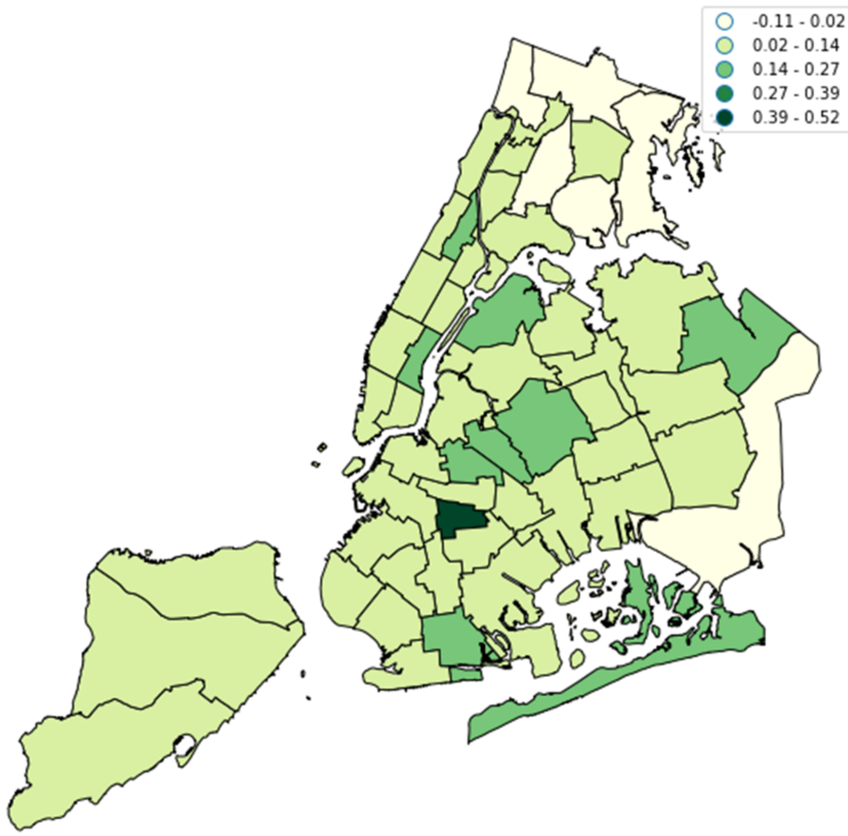

Figure 4. Tweet Sentiment Score per PUMA

The aggregated sentiment scores were mapped onto NYC to produce a choropleth, where the higher the Twitter sentiment score, the darker the colour of the PUMA is. From Figure 4, it can be observed that PUMA 4011, comprising Crown Heights South, Prospect Lefferts & Wingate, has the highest sentiment score, reflecting a higher occurrence of tweets that indicate joy and happiness compared to the rest of the PUMAs. On the other hand, we see that PUMAs 3701, 3702, 3703, 3705 and 3709 in the Bronx, and PUMA 4105 in Queens rank the lowest in New York City when it comes to tweet sentiment scores.

<u>Possible Reasons</u>
Although perhaps tenuous and not directly applicable, one possible way of measuring happiness is to look from it from the view that it (happiness) is a function of population and income growth.

4.2. Flickr Face Dataset

We next utilized the Flickr API to collect a collection of datasets of Flickr images contained within each of the PUMA. Initially, we extracted the centroid points for each PUMA and then used them as geo-coordinates for collection of geotagged images from Flickr API. Images within 5km radius from these PUMA centroids were assigned to that PUMA. For each PUMA we collected 1000 Flickr images. We then used an open source Dlib[13] face detector to select the images that contained at least one face. This allowed us to create a dataset of faces for each PUMA.

4.2.1. Visual Sentiment Methodology

Laird and Bresier (1992)[14] contends that 'the link between emotion and facial expression can be quite specific...when people produced facial expressions of fear, anger, sadness or disgust, they were more likely to feel the emotion associated with those specific expressions'. The team thus sought to empirically detect emotions using face-emotion recognition softwares.

Microsoft provides a cloud-based computer vision service called Face API[15]. It first detects human faces with a face bounding box, and with machine learning-based predictions of facial features, it will return face attribute features of predicted Age, Emotion, Gender, Pose, Smile and Facial Hair for each of the face detected in the image.

The emotions registered by the web app are: (1) Happiness, (2) Neutral, (3) Contempt, (4) Disgust, (5) Anger, (6) Surprise, (7) Fear and (8) Sadness, and returns a probability score of the person in the image reflecting the particular emotion. The total probability score will add up to a total of 1. The team attempted to test the accuracy of the Face API first by running our own images based on the eight emotions provided.

[13] "dlib C++ Library." http://dlib.net/. Accessed 29 Apr. 2019.
[14] (n.d.). The process of emotional experience: A self-perception theory.. Retrieved April 29, 2019, from https://psycnet.apa.org/record/1992-97396-008
[15] (n.d.). Face API - Microsoft Azure. Retrieved April 28, 2019, from https://azure.microsoft.com/en-us/services/cognitive-services/face/

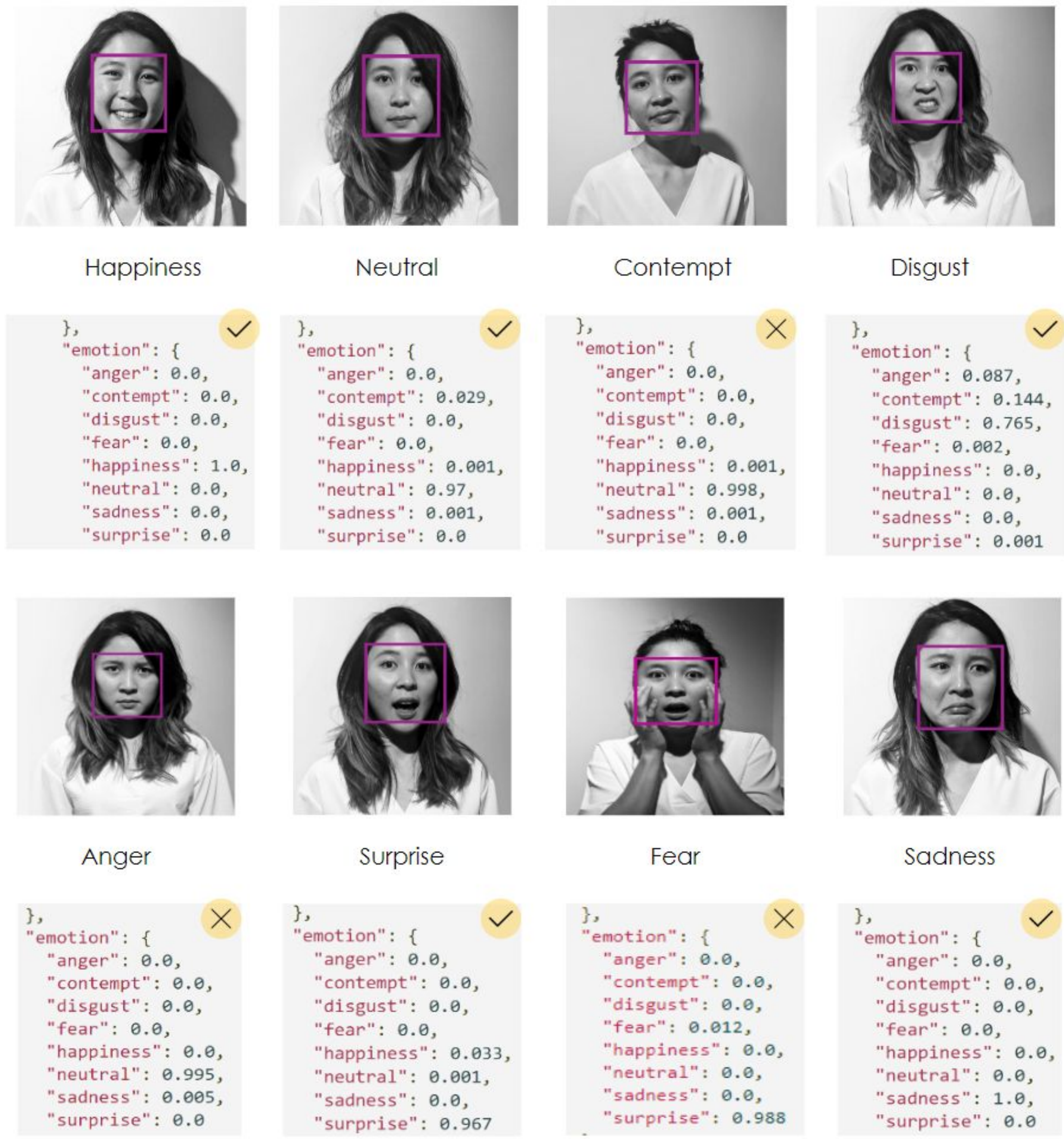

Figure 5. Testing Microsoft Face API

The API picked out ‘Happiness’ and ‘Sadness’ with a perfect probability score of 1.0. ‘Neutral’ and ‘Surprise’ were correctly identified too with the correct emotion having highest probability, 0.97 and 0.967 respectively. The algorithm did not manage to pick out ‘Contempt’, labeling it as ‘Neutral’, ‘Fear’ labelled as ‘Surprise’ as well as ‘Anger’, labeling it as ‘Neutral’. Overall the wrongly labelled emotions were deemed acceptable by the team as Neutral is classified as an impartial emotion. Furthermore, we understand that this was an introductory exploratory analysis of the API and a large dataset is required to attain statistically significant empirical evidence of the accuracy of Microsoft Face. However, this test interestingly sheds light on the idea that expression of these emotions can vary from person to person and this can affect the performance of the algorithms as they try to build generalized representation of each emotion.

Having tested Microsoft Face, we used python to query the API with face images collected from Flickr, and retrieved their emotional information. As mentioned, the API treats emotion detection as a multiclass problem and returns the probability of the following eight emotions: happiness, anger, contempt, disgust, fear, sadness, neutral and surprise. We wrote scripts to consume the API through HTTP request and extracted emotion information from our dataset of geotagged images.

Apart from performing emotion classification, we also calculated the polarity score by adding up positive emotions and subtracting negative emotions. We categorised positive, neutral, and negative emotions in the following way:

A. Positive: Happiness
B. Neutral: Neutral, Surprise
C. Negative: Contempt, Disgust, Anger, Fear, Sadness

This score ranged from -1 to 1 with -1 being extremely negative and 1 being most positive emotion. 0 would mean a neutral emotion. Finally, we aggregated our measures at PUMA level and visualized the results. An example of the emotion classification is as follows:

Figure 6. Sample image retrieved from Flickr

For Figure 6, a probability of 0.990 and 0.980 that the two faces (left and right respectively) indicated ‘happiness’ was assigned while a probability of 0.010 and 0.020 that the two faces indicated ‘neutral’ was assigned. We thus classified these two faces as ‘happiness’, while assigning each face a sentiment score of 0.990 and 0.980 respectively, achieving an aggregated score of 0.985.

Figure 7. Another sample image retrieved from Flickr

For Figure 7, a probability of 0.042 was assigned to anger, 0.132 was assigned to 'contempt', 0.01 was assigned to 'disgust', 0.094 was assigned to 'happiness', 0.715 to 'neutral' and 0.006 to 'sadness'. We thus classified this face under 'neutral' and assigned a sentiment score of -0.096.

4.2.2. Visual Sentiment Analysis

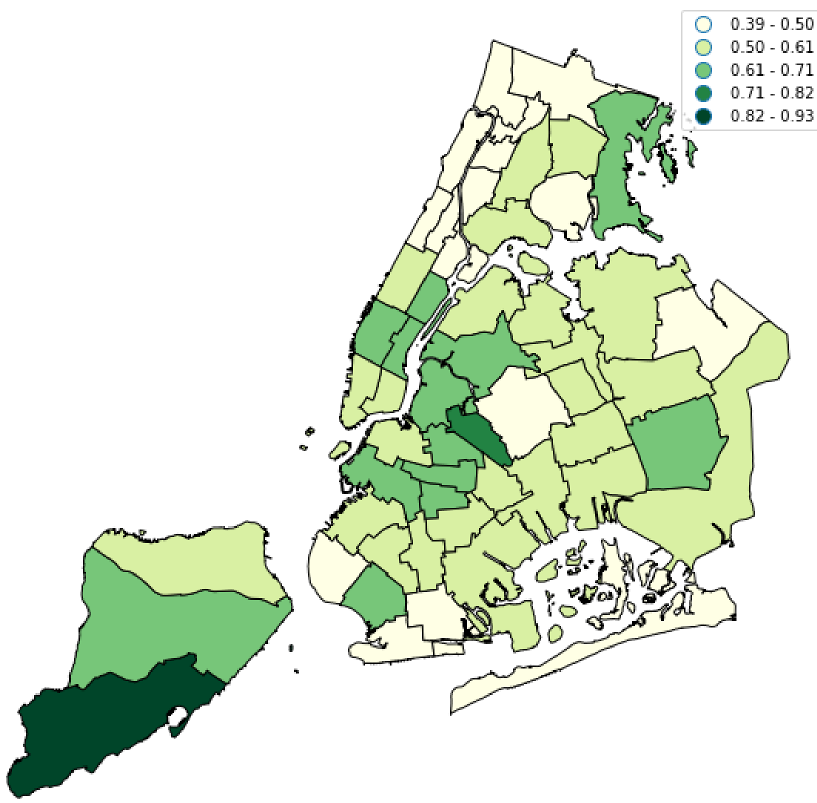

Figure 8. Flickr Sentiment Score per PUMA

The averaged sentiment scores were mapped onto New York City, where the higher the Flickr sentiment score, the darker the colour of the PUMA is. From Figure 8, it can be observed that PUMA 3901, comprising of Tottenville, Great Kills & Annadal, has the highest sentiment score, reflecting a higher occurrence of Flickr images that indicate joy and happiness compared to the rest of the PUMAs. On the other hand, we see that PUMAs located in Uptown Manhattan and the Bronx, as well as PUMAs located near the Southern edges of Brooklyn (namely PUMAs 4013 with Bay Ridge, Dyker Heights, 4016 with Sheepshead Bay, Gerritsen Beach & Homecres as well as 4018 with Brighton Beach & Coney Island) rank the lowest in New York City when it comes to Flickr sentiment scores. PUMA 4104 in Queens also ranks low here.

4.3. Relation between Tweet and Flickr Sentiments

We investigated the PUMA-wise scores for any possible relationship between the sentiments observed in tweets and flickr images for same PUMAs. We then used the pearson's correlation test to measure if there is any linear correlation between the polarity scores computed for both datasets. We found a very weak *correlation of **0.119***, but the P-value of **0.3** renders this result statistically insignificant. Thus, we did not find any conclusive evidence that similar emotions are exhibited on these platforms for similar regions. We would also like to note that given out dataset size and limited time of span for which we collected data, our results might not be representative of the broader and more stable trends. Additionally, there may be one significant event happening within one or more PUMAs, skewing the dataset with bias.

4.3.1. Spatial Relation in Tweet and Flickr Sentiments

We measure Global Moran's I to calculate the spatial autocorrelation. Global Moran's I calculates correlation between a single variable and its spatial lag. It is an indicator of global trend. Values range from -1 to +1, with positive values indicating clustering of similar values, negative values indicating dispersed trend where closer areas have different values, while 0 indicates randomness and an absence of spatial trend. For calculating, we built a Queens contiguity matrix from the PUMA shapefile. It is a simple contiguity matrix of 1-0, if two geographies touch each other it is 1 otherwise 0. Distance based matrices are better but we limit ourselves to a Queens matrix for simplicity.

Tweet Sentiment shows a Moran's I of **0.157** which shows slight clustering of similar emotions in nearby areas. With a p-value of **0.027** the result gained is deemed to be statistically significant. Some trend is also visible from the spatial lag plot shown below. The slope of the red line indicates the global moran's I.

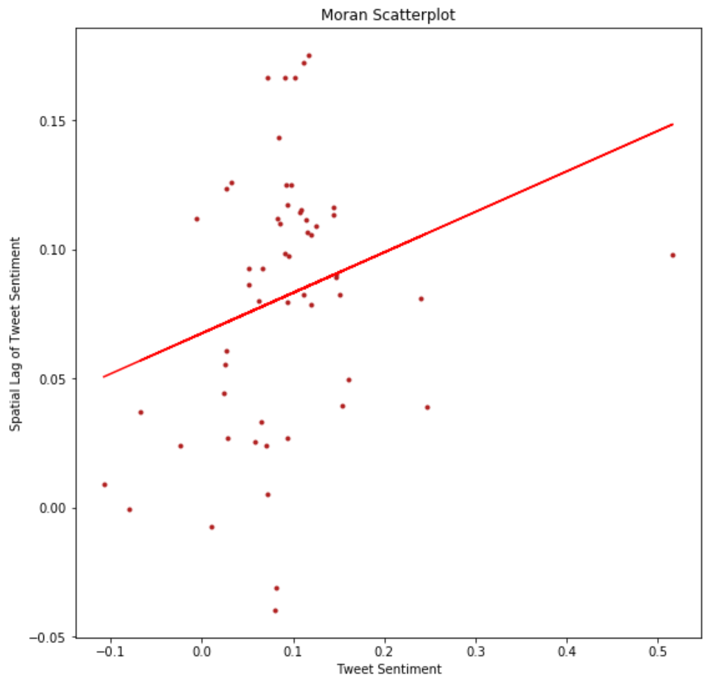

Figure 9: Spatial Lag plot Tweet Sentiment

Flickr Sentiment shows a stronger Moran's I of **0.349**, which shows a relatively stronger clustering of similar emotions in nearby areas. With a p-value of **0.001,** the result gained is deemed to be statistically significant. The spatial lag plot below shows a clearer trend. So sentiment exhibited by Flickr images has a stronger spatial autocorrelation than sentiments in tweets.

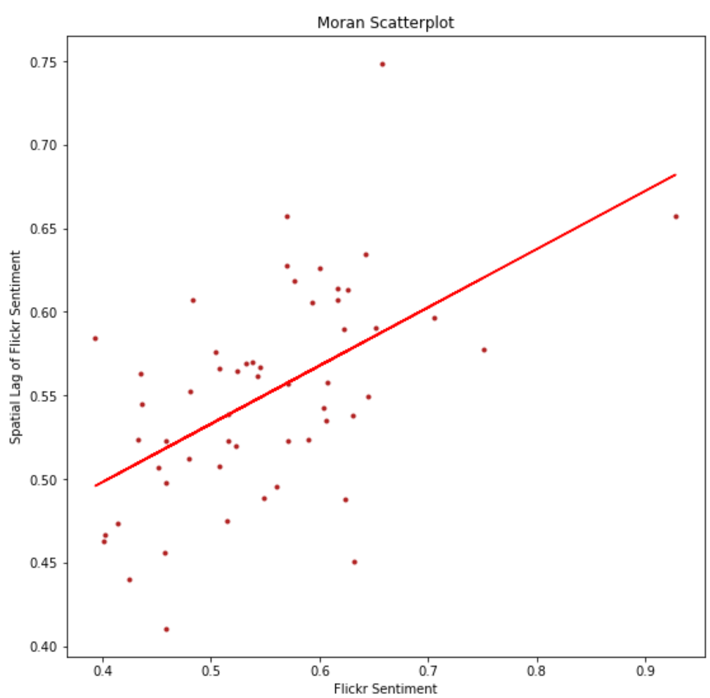

Figure 10: Spatial Lag plot Flickr Sentiment

5. Approach and Findings

5.1. Data Processing

The team collected primary data at the three sites (Brooklyn Bridge, 9/11 Memorial and Times Square) by recording 10-minute videos. Frames from these 10-minute videos were then sampled by extraction of every ten frames, translating to 1,800 frames extracted for each site. The team decided to select every ten frames, which meant that three frames were selected for every second of video recording with a 30 fps frame rate. The reason for this is so that we can reduce the chance of having blurred images representing a longer time frame, which will lead to reduced capability of expression detection. This sampling was also aimed to reduce the appearance of same person multiple times within a short frame of time. While we understand this might mean that the same pedestrian's expressions will be captured multiple times, our analysis is focused on the presence of specific emotions in relation to each other, so this should not be an issue as emotions can change frequently for every individual.

We then ran the sampled frames through Dlib's Face Detector to remove frames with no faces detected, helping reduce unnecessary wait time when we run the frames through the Microsoft Face API. We were finally left with 777 frames from the Brooklyn Bridge, 814 frames from the 9/11 Memorial and Museum, and 1668 frames from Times Square.

5.2. Emotions Detection

We utilised the Microsoft Face API again here to then extract human emotions detected in each of the three sites.

5.2.1. Brooklyn Bridge Findings and Discussion

Landmark	Happiness 🙂	Neutral 😐	Contempt 🙁	Disgust 🙁	Anger 🙁	Surprise 😐	Fear 🙁	Sadness 🙁	Sentiment (+ve minus -ve emotions)
Brooklyn Bridge	205	870	1	0	1	14	0	23	0.138265

We collected data for Brooklyn Bridge on a Thursday afternoon at 4.30pm. The sky was cloudy and there was slight drizzling. No data was detected for feelings of Disgust and Fear in the time we were there. Overall, the sentiments were positive with a nett score of +0.138 on the sentiment scale. The ratio of surprise to neutral expressions stand at 0.016.

5.2.2. Duffy Square at Times Square

Landmark	Happiness	Neutral	Contempt	Disgust	Anger	Surprise	Fear	Sadness	Sentiment (+ve minus -ve emotions)
Times Square	468	5273	10	2	5	64	0	29	0.054186

We collected data for Times Square on a Thursday afternoon at 3.30pm. The sky was cloudy but there was no precipitation. No data was detected for feelings of Fear in the time we were there. Overall, the sentiments were positive with a nett score of +0.054 on the sentiment scale. Interestingly, Times Square had the most number of data points (dictated by number of human faces detected within a 10-minute video) collected out of all three landmarks. The ratio of surprise to neutral expressions stand at 0.012.

5.2.3. 9/11 Memorial & Museum

Landmark	Happiness	Neutral	Contempt	Disgust	Anger	Surprise	Fear	Sadness	Sentiment (+ve minus -ve emotions)
9/11 Museum and Memorial	100	633	0	0	4	1	0	5	0.108501

We collected data for 9/11 Memorial & Museum on a sunny Wednesday afternoon at 1pm. No data was detected for feelings of Contempt, Disgust and Fear in the time we were there. Overall, the sentiments were positive with a nett score of +0.11 on the sentiment scale. The ratio of surprise to neutral expressions stand at 0.002

5.3. Comparison of the three landmarks

All three landmarks reported a positive sentiment score which reflects that the crowd to the three landmarks generally have more positive feelings. Times Square scored the lowest amongst the three, followed by 9/11 Memorial & Museum and then Brooklyn Bridge in terms of overall happiness sentiment. All three landmarks also did not detect 'Fear', while 'Disgust' was only detected at Times Square.

Comparing the 'Surprise' to 'Neutral' ratio also revealed that Brooklyn Bridge ranked the highest, followed by Times Square and the 9/11 Memorial and Museum. Assuming that the surprise stems from awe, this corresponds to the teams feelings on the three sites.

5.4. Comparison with sentiments online

The team collected additional Twitter and Flickr data that were specific to the three landmarks. We wanted to see if the emotions mirrored or differed for the same site in question, but across different spaces (physical as well as cyber).

5.4.1. Brooklyn Bridge

Twitter returned a sentiment score of 0.111466. Flickr returned an overall sentiment score of 0.703923.

Data Source	**Sentiment Score**
Primary Data (Collection of videos via fieldwork)	0.138275
Twitter	0.111466
Flickr	0.703923

5.4.2. Duffy Square at Times Square

Twitter returned a sentiment score of 0.112754. Flickr returned an overall sentiment score of 0.335621.

Data Source	**Sentiment Score**
Primary Data (Collection of videos via fieldwork)	0.054186
Twitter	0.112754
Flickr	0.335621

5.4.3. 9/11 Memorial & Museum

Twitter returned a sentiment score of 0.120509. Flickr returned an overall sentiment score of 0.596930.

Data Source	**Sentiment Score**
Primary Data (Collection of videos via fieldwork)	0.108501
Twitter	0.120509
Flickr	0.596930

Across the three landmarks, all of the data reflects an overall positive sentiment score. Consistently, Flickr returned the highest sentiment score out of all the three data sources across landmarks. The sentiment scores collected from our primary data were closer to the Twitter sentiment scores.

However, when we ranked these sites based on the different data sources, there is a clear correlation between our primary data and Flickr images. This could be due to the fact that they are both visual data while tweets are essentially a short string of texts.

Rank	Primary Data	Twitter	Flickr
1	Brooklyn Bridge	9/11 Memorial	Brooklyn Bridge
2	9/11 Memorial	Times Square	9/11 Memorial
3	Times Square	Brooklyn Bridge	Times Square

This leads us to several conclusions about studying Emotional Geography through online platforms:

1. Flickr is primarily an image sharing platform which has specific purposes. Taking data solely from Flickr skews reality - therein exists self-selection of positive photos since it is likely that positive photos have higher demand on flickr.
2. Twitter Sentiment score across all three landmarks are very similar, suggesting that tweets are possibly less about the geography of landmarks. People may just happen to pen down their thoughts at these places.
3. Primary observations are probably a more accurate representation of sentiments happening on the ground, although emotions should not be taken only at face value but also documented in context, including features that may affect emotions such as level of crowd, weather and sound.

6. Limitations and Future Work

Hetfield et al (1993)[16] contends that 'Vocal Feedback can also influence emotional experience' which was indeed observed by the team during fieldwork. Whilst this project only considered facial expressions from photos and videos as well as words extracted from Tweets, sound would be an interesting dimension to study. Through manual viewing of our primary data, the team actually identified instances where people were angry or annoyed, through the background sounds recorded. For instance, our video on the Brooklyn Bridge captured a cyclist clearly shouting angrily at pedestrians to get out of her way and off the bike lane. Although the video did not capture her expression, we know how she is feeling based on sound.

Another interesting angle would be the study of body languages of people, where spontaneous mimicry is also a form of emotional contagion according to Laird et al

[16] (n.d.). Emotional Contagion and Empathy Elaine Hatfield, Richard L. Rapson .... Retrieved April 29, 2019, from http://www.neurohumanitiestudies.eu/archivio/Emotional_Contagion.pdf

(1994)[17]. At the 9/11 Memorial, the team captured footage of people interacting with the North Pool. Due to the angle and position of the camera, we were unable to detect the facial expressions of some of the visitors since we could only capture their side profile. However, their body language could be an indication of their emotions and is worth studying.

Figure 11. Visitor interacting with the North Pool Memorial

The study of facial expressions as a reflection of emotions with the Microsoft Face API is limited as according to researchers from Ohio State University, humans can make more than 20 distinct facial expressions[18] and not all are captured within the 8 categories by the API.

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[17] (n.d.). Individual differences in the effects of spontaneous mimicry on .... Retrieved April 29, 2019, from https://link.springer.com/article/10.1007/BF02254830

[18] (2014, March 31). Study: Humans Can Make More Than 20 Distinct Facial Expressions .... Retrieved April 29, 2019, from https://www.theatlantic.com/health/archive/2014/03/study-humans-can-make-more-than-20-distinct-facial-expressions/359912/