Understanding Sentiments and Activities in Green Spaces using a Social Data-driven Approach

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Abstract

Green spaces are believed to enhance the well-being of residents in urban areas. While there is research exploring the emotional benefits of green spaces, most early works are based on user surveys and case studies, which are typically small in scale, intrusive, time-intensive and costly. In contrast to earlier works, we utilize a non-intrusive methodology to understand green space effects at large-scale and in greater detail, via digital traces left by Twitter users. Using this methodology, we perform an empirical study on the effects of green spaces on user sentiments, emotions and activities in Melbourne, Australia and our main findings are: (i) tweets in green spaces contain more positive and less negative emotions compared to those in urban areas; (ii) emotions in tweets vary seasonally; (iii) there are interesting changes in sentiments based on the hour, day and month that a tweet was posted; (iv) negative sentiments are typically associated with large transport infrastructures such as train interchanges, major road junctions and railway tracks; and (v) each green space is often associated with a specific type of activity and/or event, which can be a useful information for Online recommender systems. The novelty of our study is the combination of psychological theory, alongside data collection and analysis techniques on a large-scale Twitter dataset, which builds upon traditional methods in urban research and provides important implications for urban planning authorities.

Keywords: Green Spaces, Urban Areas, Empirical Study, Twitter, Sentiment Analysis, Topic Modelling, Activity Recommendation

1. Introduction

Half of the world's people are living in cities today, and the proportion of urban residents is forecasted to increase to two-thirds of the world's population by 2050 (United Nations, 2014). With this rapid urbanization throughout the world, there is an increased emphasis on understanding and enhancing the overall well-being of residents in cities and urban areas (Hartig and Kahn, 2016). Towards this objective, city planners have sought to incorporate green spaces in their urban development plans, as green spaces are believed to improve the physical and mental health of people residing in these urban areas. The emphasis on incorporating green spaces is also reflected in the United Nations Sustainable Development Goals, which include a specific target to provide accessible green space for all urban residents (United Nations, 2017). This topic has also garnered the interest of researchers in recent years (Hartig and Kahn, 2016; Schetke et al., 2016; Wang et al., 2017; Dadvand et al., 2017), and the importance of green spaces has also been highlighted with a recent perspectives article in Science (Hartig and Kahn, 2016).

Existing research has explored the emotional benefits of green spaces in urban areas (Lee and Maheswaran, 2011; Hartig et al., 2014), typically employing the use of user surveys, questionnaires and case studies. While these works have generated interesting findings on green spaces, they are often small in scale and involve the explicit participation of users. Moreover, these traditional methods are often intrusive, time-intensive and costly for researchers to perform a longitudinal study or fine-grained analysis involving participants. For example, to track users with a fine-grained resolution, personal tracking devices have to be used and worn by the participants. Similarly, to study the changes in sentiments or activities across the different days or months, surveys would need to be regularly administered over the course of the study, which is time consuming for both researchers and participants. To overcome these challenges of traditional methods, we apply sentiment analysis and topic modelling techniques on geo-tagged tweets posted by Twitter users, which serves as an unintrusive way of exploring sentiment expressed in user-generated content and is also easily available on a large scale. While we focus on green spaces in this work, our approach is easily generalizable and can be extended to examine other research questions.

Research Objectives and Contributions. In this empirical study, we aim to examine the effects that visits to green spaces have on people's sentiments and the implications of these findings for urban planning.[1] The novelty is the combination of psychological theory and analysis of digital traces left by Twitter users, which, as we will demonstrate, addresses some of the constraints of traditional methods. In particular, we will answer the following research questions (RQ).

- RQ1: How do sentiments and emotions differ in green spaces compared to urban areas?
- RQ2: How does the time of day and season of visit to green spaces affect these sentiments and emotions?
- RQ3: How does the proximity of green spaces affect these sentiments and emotions?
- RQ4: How are green spaces utilized in terms of activity types, and how can these findings be used to improve recommendations?

We apply this proposed methodology on a large set of 21.2 million tweets (2.2 million geo-tagged) to better understand the relationship between green space and user sentiments, and our main findings are:

- Tweets in green spaces exhibit higher levels of joy, anticipation and trust (positive emotions), and lower levels of anger and fear (negative emotions), compared to tweets in urban areas.
- While tweets in green spaces are generally more positive than tweets in urban areas, the season (spring, summer, autumn, winter) when a tweet was posted affects the various emotion levels differently in green space and urban areas.
- In addition, we observe interesting changes in sentiments based on the hour, day and month that a tweet was posted, which reflect trends in real-life.
- We also find a positive correlation between the sentiment polarity, i.e., degree of positivity or negativity, of tweets in urban areas and their proximity to green spaces.

[1] This chapter is an extended version of an earlier conference paper (Lim et al., 2018).

Structure and Organization. This chapter is structured as follows. Section 2 provides an overview of literature on Twitter-related analytics and green space studies. Section 3 describes our dataset collection and analysis framework. Sections 4, 5, 6 and 7 highlight the results from our experiments using Twitter, while Section 8 discusses the implications of our main findings. Finally, Section 9 concludes and summarizes the chapter.

2. Related Work

There are two streams of research that are related to our work, namely research on general Twitter-related analytics and research that examines the emotional benefits of green spaces.

General Twitter-related Analytics. As our work aims to understand the effects of green spaces on user sentiment using Twitter, we first discuss key works that are related to general Twitter analytics. Twitter is a popular micro-blogging social networking site that allows users to post short messages of 280 characters and share these tweets with their followers. In recent years, researchers have made extensive use of Twitter to understand many social phenomena and behaviours. As a form of location-based study, researchers have used Twitter to understand correlations between user mobility patterns and happiness levels (Frank et al., 2013), identify popular topics (Lansley and Longley, 2016) or witness accounts (Truelove et al., 2014) associated with various places, determine visitation rates to parks (Hamstead et al., 2018), and study travel trends across different areas (Ferrara et al., 2013). Another group of work focuses on prediction and recommendation tasks, such as predicting levels of happiness, food preferences and physical activities (Nguyen et al., 2016), predicting flu outbreaks (Achrekar et al., 2011), recommending friends (Barbieri et al., 2014), constructing interest profiles (Besel et al., 2016) and topical expertise (Wagner et al., 2012; Xu et al., 2016) of Twitter users. Other researchers focus on general applications of Twitter data in areas such as politics (Conover et al., 2011; D'Avanzo et al., 2017, Karunasekera et al., 2018), academic conferences (Wen et al., 2014), community detection (Lim and Datta, 2016), crisis management (Kavanaugh et al., 2012), crowd sensing (Roitman et al., 2012), event detection (Cui et al., 2012; Popescu and Pennacchiotti, 2010; Xie et al., 2016), among others.

Analysis of Psycho-social Response to Green Spaces. We now discuss key works related to the various aspects of understanding green spaces in urban areas. The study of green spaces in urban areas have garnered strong interest in recent years (Hartig and Kahn, 2016; Schetke et al., 2016; Wang et al., 2017; Dadvand et al., 2017), ranging from determining the appropriate levels of green spaces (Wolch et al., 2014) to understanding the usage patterns of urban green spaces (Schetke et al., 2016). Among these works, we are most interested in works that study the effects of green spaces on people in urban areas. Many of these works utilized surveys or questionnaires to understand how green spaces affect a range of different outcomes related to personal wellbeing (Chiesura, 2004), thermal comfort (Wang et al., 2017), life expectancy of residents (Takano et al., 2002), and prevalence of myopia (Dadvand et al., 2017). Researchers (Roe et al., 2013; Tyrvainen et al., 2014) augmented these surveys with clinical measurements to study the correlations between green spaces and stress level, via measurements of blood pressure and salivary cortisol levels. Others (Al-Husain et al., 2013) have also used wearable biosensors to study the physiological response of users to different types of environments. However, green space research typically relies on traditional methods based on surveys, questionnaires, case studies or wearable sensors, and has not previously used twitter data analytics to explore user sentiment. This observation is supported by recent comprehensive literature surveys of existing work on the benefits of green spaces (Lee and Maheswaran, 2011; Hartig et al., 2014).

Discussion. While previous research has examined interesting aspects of Twitter and green spaces separately, we note two key differences with our study, namely: (i) while the works using Twitter-related analytics present interesting and useful understanding of some social phenomena, our work examines the relationship between green spaces and people's sentiments in multiple aspects, such as time, proximity, activity types, and demonstrates how these findings help to improve recommendations; and (ii) many early studies on green spaces and their associated health and well-being outcomes are based on surveys, questionnaires or case studies, which are typically small in scale, intrusive, time-intensive, costly, and difficult to replicate. In contrast, our study utilizes a big data driven framework based on implicit digital traces left by Twitter users, which is large in scale and non-intrusive, to study how green spaces affect user sentiments across different time periods and spatial areas. In addition, our proposed framework can be easily extended to study other research questions, e.g., understanding general sentiments about the "La La Land" movie by analyzing tweets with the "#LaLaLand" hashtag, or sentiments regarding specific areas by examining geo-tagged tweets posted in those areas.

3. Experimental Design

Figure 5.1 illustrates our data-driven approach to studying green space, which comprises the main steps of data collection, tweet pre-processing, sentiment analysis, and topic/activity detection that are described in Sections 3.1, 3.2, 3.3 and 3.4, respectively.

3.1. Dataset and Data Collection

Our dataset comprises a set of 21.2 million tweets (2.2 million geo-tagged) generated by 10,510 users in Melbourne, Australia. We also have access to a green space dataset, comprising the locations and coverage of 482 green spaces (e.g., parks, gardens, green fields and other open areas) in this city.

Table 5.1. Description of Dataset

Number of Users	10,510
Total Tweets	21.2 million
Geo-tagged Tweets	2.2 million

Twitter Dataset. We first describe our data collection methodology for the Twitter dataset, which was collected from Nov 2016 to Jan 2017 using the Twitter REST API. For this dataset, we employed a two-stage collection as follows:

1. **Stage 1 Collection**: This initial stage involves collecting all geotagged tweets (i.e., tagged with latitude/longitude coordinates) that are posted within a 5km × 5km grid in central Melbourne, Australia. This 5km × 5km grid is centered on approximately the Melbourne GPO building. Figure 5.2 illustrates this data collection process where a series of overlapping circle-based Tweet searches ensures comprehensive coverage of the whole 5km × 5km grid. We experimented with various other approaches and found this approach, i.e., using overlapping circle-based Tweet searches with a radius of 400m, performs the best in terms of retrieving a high proportion of geo-tagged tweets.
2. **Stage 2 Collection**: Based on the set of retrieved geo-tagged tweets (from Stage 1), we then proceed to extract the list of unique Twitter users who have posted these tweets, i.e., a set of seed users who have posted tweets in Melbourne, Australia. Thereafter, we retrieve the most recent 3,200 tweets of these users, as per Twitter API constraints, to build a tweeting profile for these users. Table 5.1 shows the statistics of this collected dataset, while Figure 5.3 illustrates the geographical distribution of these tweets.

3. **Green Space Dataset**. We also have access to a green space dataset, provided by the City of Melbourne, which is the local government authority in charge of urban planning and regulations for the central

Melbourne area. This dataset is in the form of a GeoJSON file that comprises 482 green spaces in Melbourne. These green spaces are represented by polygons, which encompasses the entire and exact area of each green space.

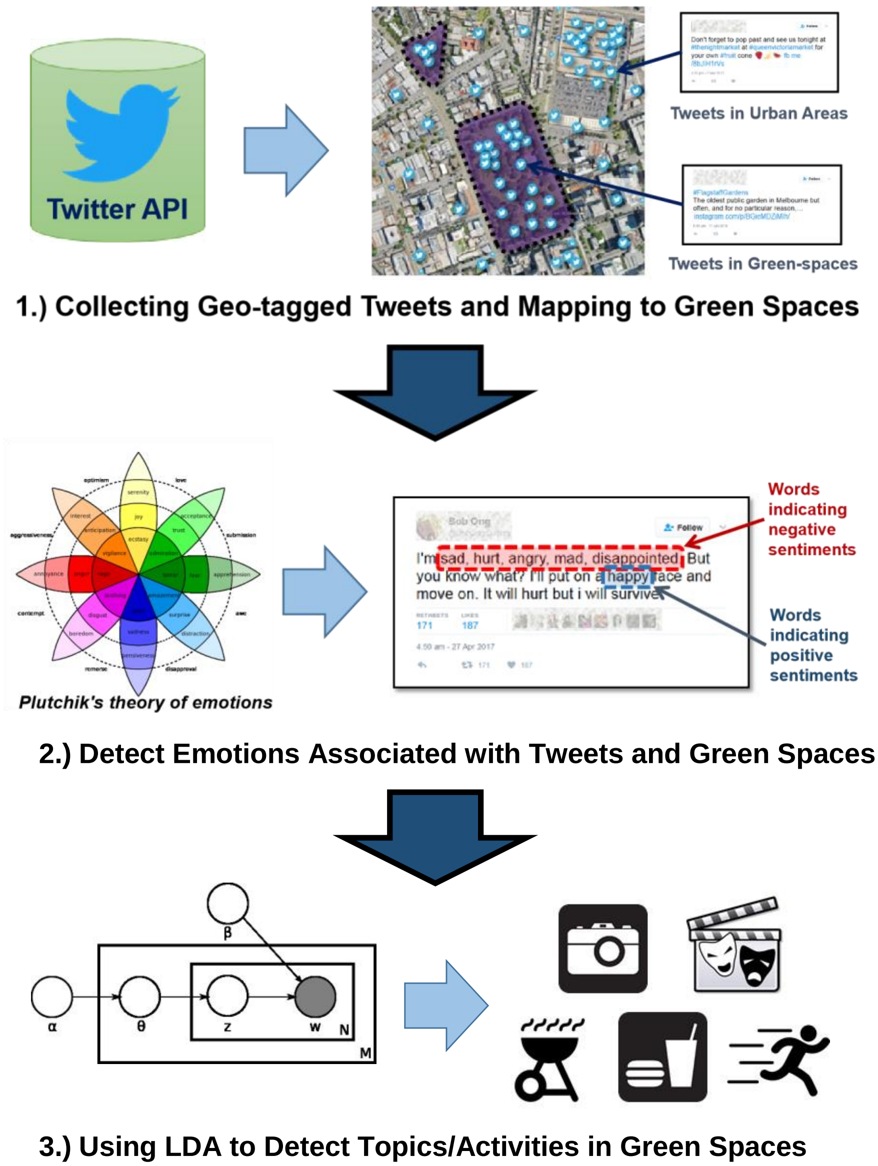


Figure 5.1: Overview of our approach to green space analysis.

Mapping Tweets to Green Spaces. We also identified: (i) if a tweet was posted in a green space, which park was it posted from; and (ii) if this tweet was not posted in a green space, how far was it from the nearest green space.

Using our collected tweets and green space dataset, we then labelled each tweet with the ID of the green space that these tweets were posted from. For tweets that were not posted from a green space (i.e., posted from an urban area), the distance to the nearest green space and the ID of this green space was identified.

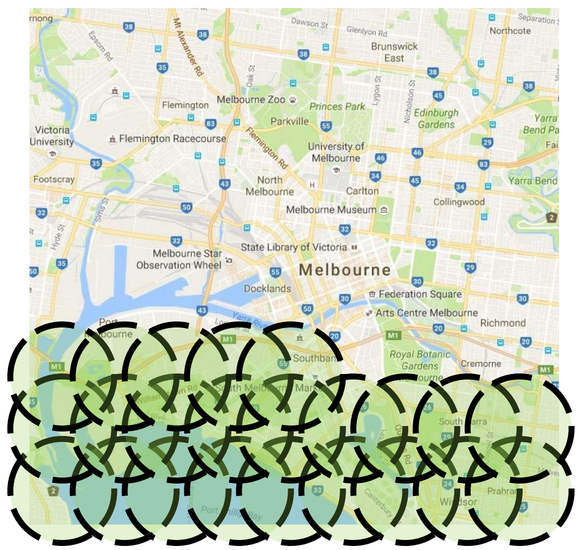


Figure 5.2: Tweet Collection using overlapping circle-based searches. A single iteration of this collection starts from the bottom left and continues until the entire area is covered, before repeating itself for the entire duration of data collection.

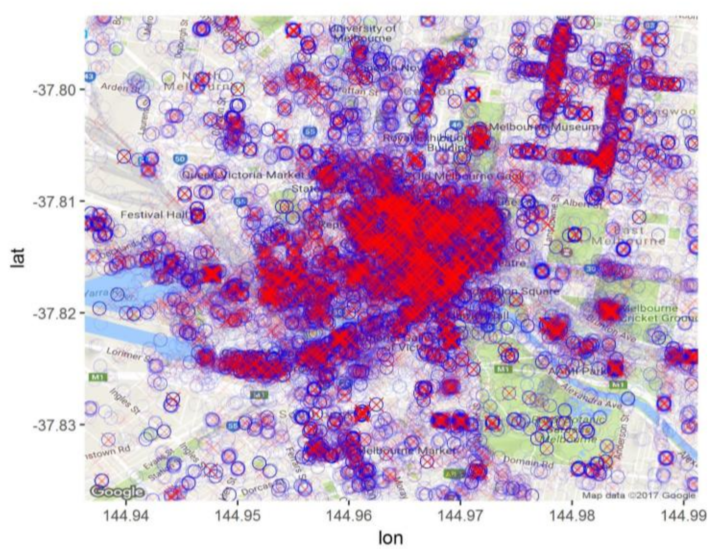


Figure 5.3: Geographical distribution of tweets in our dataset.

3.2. Data Preprocessing

Prior to performing our sentiment analysis on the tweets, we perform a number of pre-processing steps on the collected tweets. We restrict our work to using tweets that are explicitly geo-tagged as such tweets allow us to determine where they are posted from. These steps include the following:

- Filtering tweets that are explicitly geo-tagged with latitude and longitude coordinates and within the 5km × 5km grid in Melbourne, Australia.

- Selecting tweets that are written in English, based on the "language" field provided by the Twitter API. We chose to only consider English tweets as English is the main language spoken in the Australia and more importantly, focusing on one language allows us to abstract away the nuances associated with sentiment analysis based on different languages.[2]

- Tokenizing each tweet into individual words based on separation by white-spaces.

- Converting all tweets and tokenized words into lower-case.

3.3. Sentiment Analysis

We utilize a commonly used sentiment analysis technique (Bollen et al., 2011; Le et al., 2017), which involves first splitting each tweet into a series of tokens/words, then comparing each token/word to determine the sentiment category in which they belong to. Similar to these earlier work, we calculate sentiment score $Senti^S_t$ of a tweet t based on the word usage frequency of each sentiment category S. To account for different tweet lengths, we normalize each sentiment score $Senti^S_t$ by the number of words in each tweet. More formally, given a list of words $w \in t$ and a specific sentiment type S, the sentiment level of a tweet t is calculated by:

$$Senti_t^S = \frac{|w \in t \cap S|}{|t|} \tag{1}$$

[2] Although we focus on English tweets in this work, this work can also be easily extended to any text-based social media written in other languages by using a sentiment dictionary of that language. Furthermore, this work focuses on the text/words used in tweets and future work can also consider the embedded links, photos and videos using image recognition techniques.

Based on this definition, the calculated sentiment level will take on a value in the range of [0,1], with 0 and 1 representing the weakest and strongest levels of the sentiment, respectively. For these sentiment categories, we utilize the NRC Word-Emotion Association Lexicon (EmoLex) (Mohammad and Turney, 2013, 2010), which is a widely used emotion word lexicon due to its rich vocabulary. EmoLex has also been used in numerous research for sentiment analysis purposes (Aiello et al., 2016; Quercia et al., 2016; OrellanaRodriguez et al., 2015). EmoLex comprises 10,170 words that are associated with the emotions of anger, anticipation, disgust, fear, joy, sadness, surprise and trust, introduced in Plutchik's theory of emotions (Plutchik, 1980). Figure 5.4 illustrates Plutchik's theory of emotions, where each leaf indicates an emotion category (terror, fear, apprehension) with the inner and outer most quadrants showing the highest and lowest intensity of that emotion category, respectively.

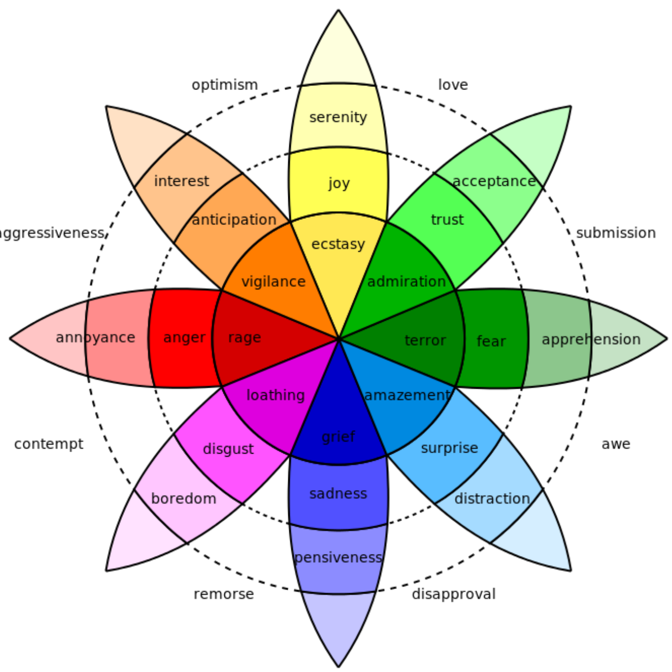


Figure 4: Plutchik's Wheel of Emotions (Plutchik, 1980). Retrieved from Wikipedia (Wikipedia, 2017).

As pointed out in (Mohammad and Turney, 2013), the emotions of anger, disgust, fear and sadness are generally associated with negative sentiments, while the emotions of anticipation, joy and trust are generally associated with positive sentiments. The emotion of surprise is neutral, i.e., can belong to either category, and hence is used independently but not for the calculation of positive or negative sentiments. Thus, we define another two sentiment categories of positive (comprising the emotions of anger, disgust, fear and sadness) and negative (comprising the emotions of anticipation, joy and trust). We define the positivity and negativity level of a tweet *t* as follows:

$$Senti_t^{Neg} = \frac{|w \in t \cap S^{Neg}|}{|t|} \tag{2}$$

$$Senti_t^{Pos} = \frac{|w \in t \cap S^{Pos}|}{|t|} \tag{3}$$

where sentiment type S^{Neg} = {*anger, disgust, fear, sadness*}, and sentiment type S^{Pos} = {*anticipation, joy, trust*}.

It should be noted that a tweet can be both positive and negative based on the words used. For example, consider the tweet "A wonderful day for a picnic! The heat is horrible but it's great that the weather cooled down!". This tweet has both positive and negative sentiments based on the words, "wonderful" (positive), "horrible" (negative) and "great" (positive).

To address the issue of tweets with both positive and negative sentiments, we adopt a similar approach as (Le et al., 2017) and determine the polarity of a tweet based on the difference between the positive and negative sentiment scores of a tweet. Thus, the polarity of a tweet *t* is defined as:

$$Senti^{t}_{Pol} = Senti^{t}_{Pos} - Senti^{t}_{Neg} \tag{4}$$

To verify this sentiment analysis approach, we also compared this method against various algorithms, namely those proposed in (Goodrich et al., 2016; Liu et al., 2005; Hu and Liu, 2004; Nielsen, 2011). The results show a similar trend in terms of the derived tweet sentiments regardless of the algorithm used, thus validating the general performance of our sentiment analysis approach against other similar algorithms.

3.4. Identifying Topics/Activities in Parks

Next, we describe our approach for understanding the main topics/activities in parks. Similar to (Lim et al., 2017), we apply a topic modelling algorithm, Latent Dirichlet Allocation (LDA) (Blei et al., 2003), on all tweets in each park to determine the main topics and activities that take place in these parks.

Given that each tweet t is represented by a sequence of words $w \in t$ and w_n denotes the n^{th} word in the tweet, LDA applies a generative process for each tweet t, as follows (Blei et al., 2003):

1. Choose $N \sim$ Poisson(ξ).
2. Choose $\theta \sim$ Dir(α).
3. For each of the N words w_n:
   (a) Choose a topic $z_n \sim$ Multinomial(θ).
   (b) Choose a word w_n from $p(w_n|z_n,\beta)$, a multinomial probability conditioned on the topic z_n.

The general idea behind the LDA algorithm is that it represents each topic/activity as a bag-of-words (i.e., a set of individual words), and each tweet is represented by a set of topics with varying probabilities.

4. RQ1: Green Space Effects

In this section, we aim to address RQ1 on the effects that green spaces have on the sentiments and emotions in such green spaces, compared to tweets posted in urban areas.

4.1. Comparison of Tweet Sentiments in Green Spaces Versus Urban areas

We first examine the presence of any significant difference in mean sentiment (positive, negative, polarity) between tweets posted in green spaces and those posted in urban areas. Table 5.2 shows the average sentiment level of tweets posted in green space and urban area, and associated p-values. In particular, the column "difference" indicates the increase in a specific sentiment level of tweets in green space over that of urban areas, the reported p-values are based on a two-sided Student's t-test.[3]

Table 5.2. Comparison of tweet sentiments in green spaces and urban areas. The bold numbers indicate a statistically significant difference.

Sentiment Type	Greenspace	Urban Area	Difference	p-value
negative	.0300	.0318	**-5.60%**	<.0001
positive	.0815	.0764	**6.79%**	<.0001
polarity	.0515	.0446	**15.62%**	<.0001

[3] This "difference" is calculated by dividing the mean sentiment levels in green spaces over that of urban areas, and the reported values are based on the exact (non-rounded) sentiment levels for a higher precision, whereas the values reported in the tables are rounded to the nearest 4 decimal points for brevity.

Table 5.2 shows that there is a statistically significant increase ($p < .0001$) of more than 15% in the polarity of tweets posted in green spaces, compared to those in urban areas. Similarly, there is a statistically significant decrease ($p < .0001$) of more than 5% in the negativity of tweets posted in green spaces, and also an increase of more than 6% in the positivity of tweets. These results show that green spaces generally benefit from higher positivity and lower negativity, compared to urban areas, and we examine more specific emotions in the next section.

4.2. Comparison of Tweet Emotions in Green Spaces Versus Urban areas

Similar to Section 4.1, we performed a two-sided Student's t-test to compare if there is any difference in each emotion level between tweets posted in green spaces and those in urban areas. The results are shown in Table 5.3, and the columns are similarly defined as those in Section 4.1. In contrast to Section 4.1 that examines how positive or negative the tweets are, this section examines a more detailed breakdown of the sentiments into specific emotions, which are discussed later.

Based on our analysis, we find that there is an increase of more than 10% in joy and decrease of approximately 10% in both the fear and anger emotions, for tweets posted in green spaces compared to their counter-part in urban areas. There is also an increase of 6.5%, 5.6% and 2.95% for the trust, surprise and anticipation emotions, respectively. The reported difference in the emotions of joy, fear, anger, trust, surprise and anticipation are also statistically significant, with p-values of less than 0.0001. While there are differences in the emotions of disgust and sadness, these differences are not statistically significant with p-values of more than 0.05.

Table 5.3. Comparison of tweet-level emotions in green spaces and urban areas. The bold numbers indicate a statistically significant difference.

Sentiment Type	**Greenspace**	**Urban Area**	**Difference**	**p-value**
anger	.0071	.0079	**-9.75%**	<.0001
anticipation	.0264	.0256	**2.95%**	<.0001
disgust	.0051	.0053	-3.13%	.05689
fear	.0085	.0095	**-10.27%**	<.0001
joy	.0300	.0271	**10.62%**	<.0001
sadness	.0093	.0092	1.39%	.24705
surprise	.0129	.0122	**5.60%**	<.0001
trust	.0252	.0236	**6.54%**	<.0001

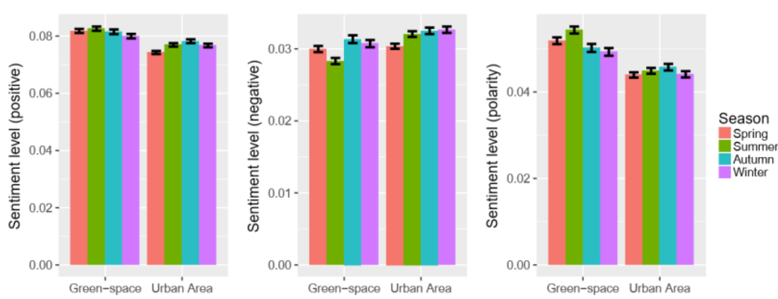
Section 4.1 shows that green spaces generally display higher positivity and lower negativity than urban areas, and there are higher levels of positive emotions of joy, trust and anticipation, and lower levels of negative emotions of fear and anger in green spaces than urban areas. For the negative emotions of disgust and sadness, there is insufficient evidence to indicate any differences between green spaces and urban areas. We now explore how these sentiments and emotions change over various time periods.

5. RQ2: Impact of Time

In this section, we perform a longitudinal study of sentiments and emotions across time periods of different seasons and, in finer-grained time steps, of time of day and month.

5.1. Comparison of Sentiments and Emotions across Seasons

For our analysis of sentiments and emotions across the four seasons, we label a tweet as belonging to a particular season if this tweet was posted within the three months of the season, as widely used in Melbourne, Australia: Spring (Sep-Nov), Summer (Dec-Feb), Autumn (Mar-May), Winter (June-Aug).



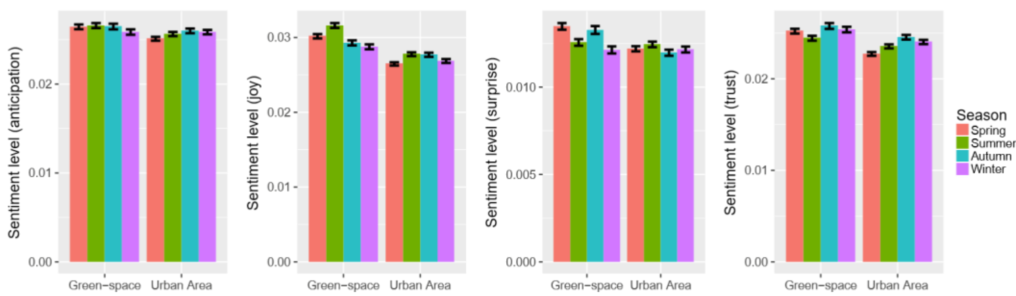
(a) (b) (c)

Figure 5.5: Longitudinal study of tweet sentiments across the four seasons.

5.1.1. Comparison of Sentiments Across Seasons

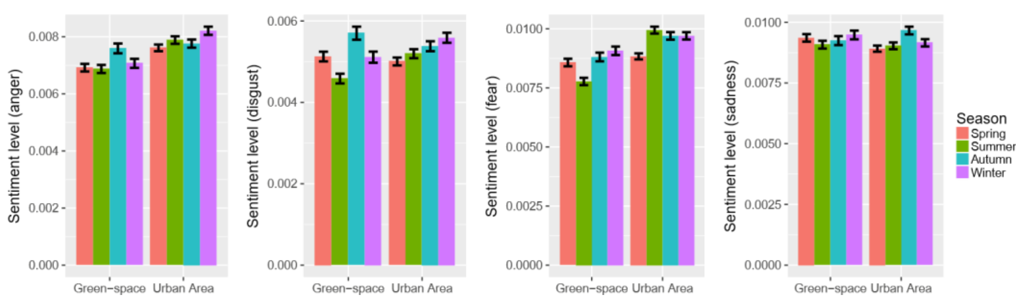
We start our longitudinal study on tweet sentiments by first examining the level of positive, negative and polarity of tweets posted across the four seasons in green spaces and urban areas, as shown in Figure 5.5. When examining levels of positive (Figure 5.5a) and negative sentiments (Figure 5.5b), we note that positive sentiments are higher and negative sentiments are lower in green spaces compared to urban areas, across all seasons of spring, summer, autumn and winter. For both tweets in green spaces and urban areas, we also observe that negative sentiments are the highest in autumn and winter, a trend that resembles the seasonal affective disorder where "depressive symptoms occur during the winter months"[4] (Rastad et al., 2006; Rosenthal et al., 1986).

Recall that a tweet can contain both positive and negative sentiments (as described in Section 3.3), hence we use the polarity of a tweet to better measure the positivity or negativity of a tweet on its own. Figure 5.5c shows that the polarity levels of tweets posted in green spaces are higher (more positive) compared to those in urban areas, regardless of the season when a tweet is posted. In particular, we observe that tweets posted in green spaces are the most positive in summer, followed by spring, autumn and winter, in an order corresponding to the temperatures associated with each season. The polarity of these tweets gives us an overview of the positivity and negativity of tweets, and we examine the emotions associated with these tweets in the following sections.



(a) (b) (c) (d)

Figure 5.6: Longitudinal study of tweet emotions (positive only) across the four seasons.



(a) (b) (c) (d)

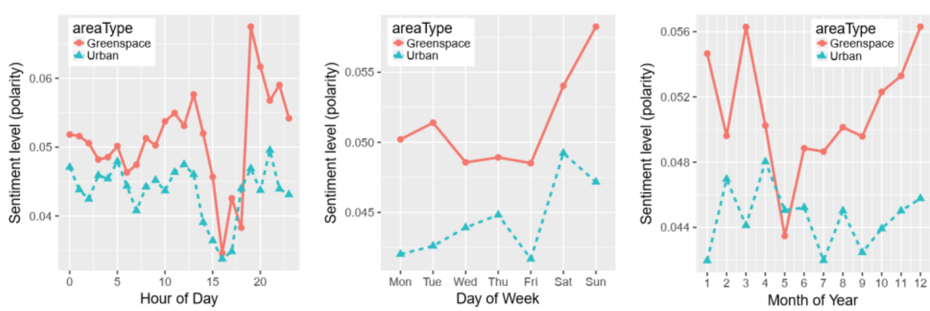
Figure 5.7: Longitudinal study of tweet emotions (negative only) across the four seasons.

[4] In the study by Rastad et al. (Rastad et al., 2006), they consider that "winter was defined as the combination of autumn and winter seasons".

5.1.2. Comparison of Emotions Across Seasons

Figure 5.6 shows the average level of emotions for anticipation, joy, surprise and trust for tweets posted across the four seasons in green spaces and urban areas. The results for these positive emotions are similar to that in Section 5.1.1, as tweets in green spaces show higher levels of anticipation, joy, surprise and trust, compared to those in urban areas in the same season. Figure 5.6b shows that the emotion of joy is most prevalent out of all four emotions, with the highest levels for tweets in both green spaces and urban areas. In general, the results show that tweets in green spaces evoke more positive emotions of anticipation, joy, surprise and trust.

Next, we examine the average levels of emotions for anger, disgust, fear and sadness, as shown in Figure 5.7. In terms of the emotions of anger (Figure 5.7a) and fear (Figure 5.7c), tweets in green spaces show lower levels of these negative emotions, compared to its counterparts in urban areas in the same season. In terms of the emotions of disgust (Figure 5.7b) and sadness (Figure 5.7d), we observed mixed results where there are no clear "winners" between tweets posted in green spaces and urban areas, i.e., green spaces exhibit lower levels of these emotions in some seasons but not others. In all cases for tweets in green spaces, we note that the lowest levels of anger, disgust, fear and sadness are found during summer, an observation similar to that of the seasonal affective disorder where depressive symptoms are less likely during summer months (Rastad et al., 2006; Rosenthal et al., 1986).



(a) (b) (c)

Figure 5.8: Longitudinal study of tweet sentiments based on the hour of day (left), day of week (middle) and month of year (right) that a tweet was posted. Scales do not start from zero for a clearer comparison.

5.2. Comparison of Sentiments Across Hours, Days and Months

After examining how sentiments change across the seasons, we now examine how these sentiments change across finer time periods of hours, days and months, as shown in Figure 5.8.

In terms of sentiments change across the hours of the day (Figure 5.8a), e.g., 12am, 1am, 2am, etc, we notice that the sentiment polarity of tweets becomes lower (more negative) from approximately 12-1pm onward until reaching a trough at 4-5pm, before increasing drastically thereafter. While this trend applies to both green spaces and urban areas, the change during this time period is more pronounced for tweets in green spaces. We attribute this due to the fact that most people are either at work (or school) from 8am to 5pm, and they become more negative towards the end of this work cycle, i.e, 12pm to 4 pm. However, the recovery period (work detachment and relaxation) takes place at the end of this work cycle (Sonnentag et al., 2008) and sentiment of the person improves through the evening, i.e., 5 pm onwards. Similarly, social scientists have also noted that "positive emotion runs high in the morning, declines throughout the day, and rebounds in the evening" (Miller, 2011).

Figure 5.8b shows the change in sentiment based on the day of the week. Psychological studies have shown that people tend to be happier during weekends (Stone et al., 1985) and our Twitter-driven study shows the same observation, as indicated by higher levels of sentiment polarity during Sat and Sun for both green spaces and urban areas. While there is a trend of more positivity during weekends, we also observe that tweets are consistently more positive in green spaces compared to urban areas, regardless of the day a tweet was posted.

The sentiment changes across the months (Figure 5.8c) show that sentiments in green spaces are the lowest (most negative) in May, i.e., the end of Autumn, before gradually increasing to a peak in December, i.e., the start of summer. While there are some variations in tweet sentiments in urban areas, we note that there are no obvious trends in sentiment change for urban areas. These results show a finer grained analysis of how sentiments change across the months, while displaying the same general trends of how sentiments change across the broader seasons (as discussed in Section 5.1.2).

6. RQ3: Green Space Proximity Effect

In this section, we investigate the effects of green space proximity by performing a high-level study of sentiments in broad city grids and studying the correlation between sentiments in urban areas and their proximity to green spaces.

6.1. Grid-based Analysis

For a broader-scale understanding of sentiments in Melbourne, we perform a grid-based analysis of sentiment polarity within the same city, where each 250m grid comprises the aggregated sentiment polarity of all tweets within that grid. Figure 5.9 shows the result of this analysis where blue grids indicate positive sentiments and red grids indicate negative sentiments, while deeper colours indicate a higher level of that sentiment.

Figure 5.9 shows that most of the grids with negative sentiments are relating to areas that contain large transport infrastructures (train stations, road junctions, railway tracks) or residential areas. Most of the grids containing green spaces exhibit positive sentiments with the exception of one grid that contains a hospital (which has since shifted), where most tweets mention about visiting patients or going for their cancer treatments.

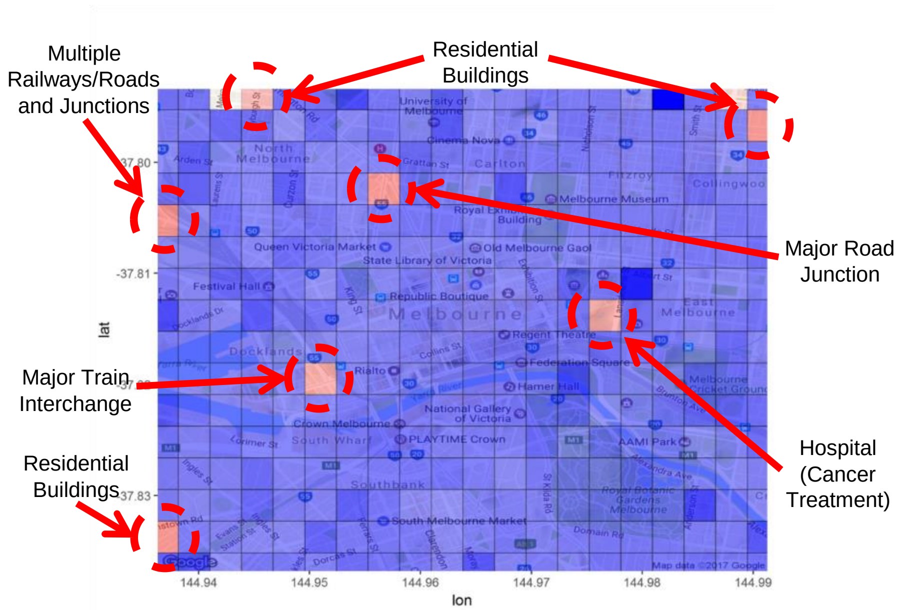


Figure 5.9: Grid-based Sentiment Analysis.

6.2. Proximity of Green Spaces and Urban Sentiments

To understand how the proximity of green spaces affects user sentiments in urban areas, we calculate the Pearson correlation coefficients between the sentiment levels of urban tweets and their distance to the nearest green space. Tables 4 and 5 show the results of this correlation test in terms of sentiments (positive, negative, polarity) and emotions (anger, anticipation, disgust, fear, joy, sadness, surprise and trust), respectively.

Table 5.4. Pearson Correlation of Sentiments and Distance to Nearest Green Space. The bold numbers indicate a statistically significant correlation.

Sentiment	**Correlation**	**p-value**
negative	**-0.0150**	<.0001
positive	0.0003	.90918
polarity	**0.0091**	.00017

The results (Table 5.4) show a significant negative correlation between negative sentiments and green space proximity ($p < .0001$), and a significant positive correlation between sentiment polarity and green space proximity ($p = .00017$) but none for positive sentiments. Table 5.5 shows that anger, anticipation, fear, sadness and trust are negatively correlated with green space proximity ($p < .0001$ for all, $p = .00655$ for sadness), while joy is positively correlated ($p < .0001$). These results show that while green spaces have an effect on urban areas, this effect is significant in terms of a reduced negative sentiment, but not significant in terms of an increase in positive sentiments.

Table 5.5. Pearson Correlation of Emotions and Distance to Nearest Green Space. The bold numbers indicate a statistically significant correlation.

Sentiment	Correlation	p-value
anger	**-0.0111**	<.0001
anticipation	**-0.0103**	<.0001
disgust	-0.0011	.64589
fear	**-0.0244**	<.0001
joy	**0.0191**	<.0001
sadness	-0.0066	.00655
surprise	0.0031	.19721
trust	**-0.0094**	<.0001

7. RQ4: Activities, Sentiments and Recommendations

In this section, we focus on nine popular parks (Table 5.6) within inner Melbourne, and study the different activities and sentiments associated with these parks. We also discuss how these findings can be used to improve recommendations of green spaces.

Table 5.6. Parks and Tweets

Green Space	Description	# Tweets
Batman Park	Small park located north of Crown Casino	727
Birrarung Marr	Park located along Yarra river	1322
Carlton Gardens	Large park that is listed as a World Heritage Site	4565
Domain Parklands	Network of various connected parks and reserves	5026
Enterprize Park	Very small park (~60m×40m) along Yarra river	1112
Flagstaff Gardens	Large park in the office district	1197
Parliament Reserve	Small triangular park in the city	827
State Library Forecourt	Small green patch at the State Library of Victoria	6623
Yarra Park	Large park that includes the Melb. Cricket Grounds	5963

7.1. Activities and Sentiments

Consistent with our earlier results, we found that none of the studied parks evoke an overall negative sentiment, i.e., polarity<0. While all parks generate positive sentiments, they evoke different levels of emotions based on the types of activities that take place in each park. For example, Yarra Park evokes high levels of trust likely due to the confidence of supporters in their sporting teams during the respective matches. Figure 5.10 and Table 5.7 show that both the #hashtag wordcloud and activity/topic analysis are able to pick up the two main sports of Cricket and Football. For example, hashtags and words like gopies, gotiges and gostars are frequently used in support of the various sporting teams.

Table 5.7. Activities/Topics in Yarra Park.

Activity	Words Used	Polarity
Cricket	mcg,ground,cricket,game,mcc,night,happy,cwc,carlton	0.1211
Sports	mcg,cricket,mcc,afl,football,gopies,win,team,footy,gotiges	0.0995
Sports	cricket,ground,mcg,east,today,just,others,mcc,members	0.0405

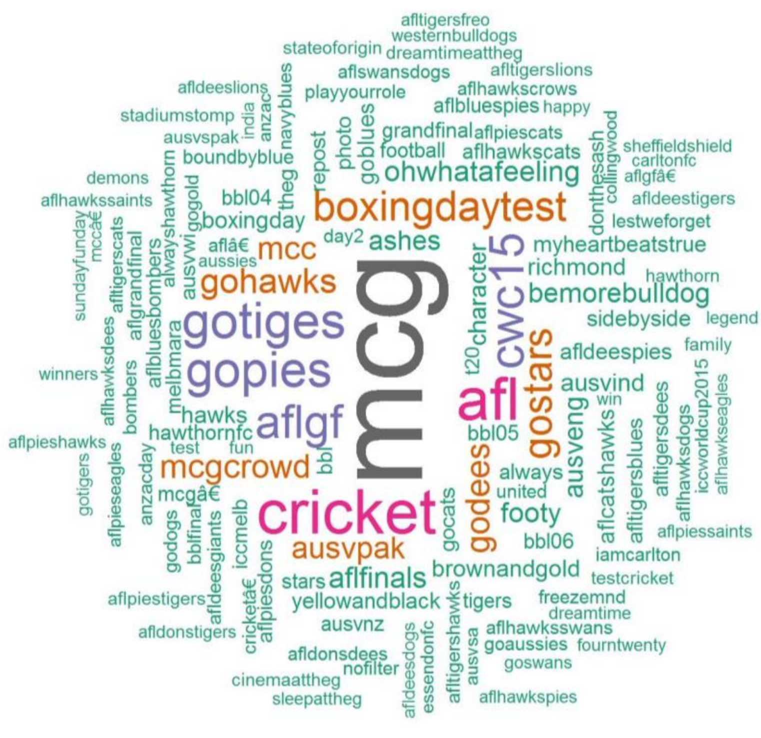


Figure 5.10: Wordcloud of Twitter hashtags used in Yarra Park.

In the interest of space, we summarize our two main findings in terms of the activities and sentiments observed in these parks, which are: (i) The most common activities that occur in larger parks are Food, Drinks and Events, with all activities being associated with positive sentiments. The only exception is Flagstaff Gardens, where the Education activity shows a slight negative sentiment, while other activities in the same park are positive; and (ii) Another observation is that parks with a rich historical background or containing prominent landmarks show #photo as the most popular hashtag (Figure 5.11), e.g., Carlton Gardens and Flagstaff Gardens, indicating that photography is another popular activity in those places.

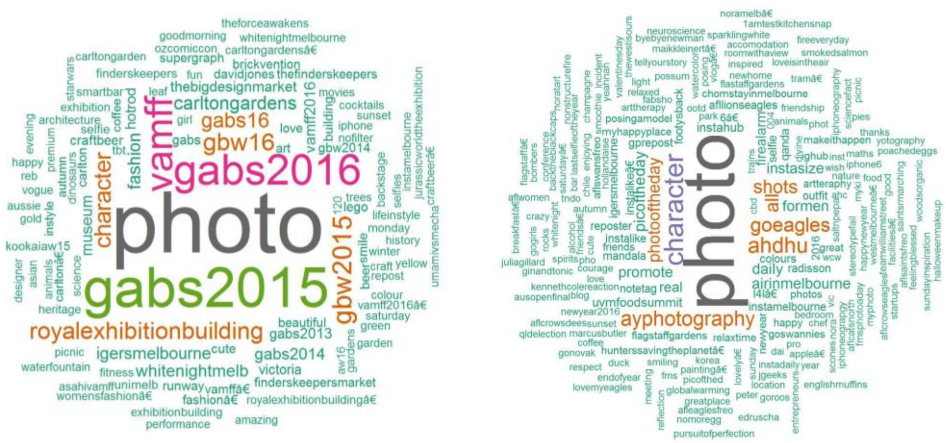


Figure 11: Wordcloud of Twitter hashtags used in Carlton Gardens (left) and Flagstaff Gardens (right).

7.1. Sentiment-aware Activity Recommendations

Building upon our previous finding that different green spaces are associated with different types of activities, we now examine how these results can be used to improve recommendation systems. We extended upon these results in (Wang et al., 2018), and grouped activities into three main categories of Workout (e.g., jog, run), Relaxation (e.g., meditation, chill) and Social (e.g., hangout, party) using a supervised approach. Our main finding is that the sentiments and popularity of different activities vary widely throughout the year and in different green spaces, i.e., no single green space is consistently popular for the same activity through the year.

Based on this earlier observation, we developed a sentiment and activity aware recommendation system for green spaces, as shown in Figure 5.12. This system considers the preferences and context of the user to recommend green spaces that are popular for specific activities based on this context. This system first solicits user input (context) based on the preferred visit time, current location, travel distance and desired activities (Figure 5.12, top half), before recommending the top three green spaces (Figure 5.12, bottom half) based on a combined popularity and sentiment score.

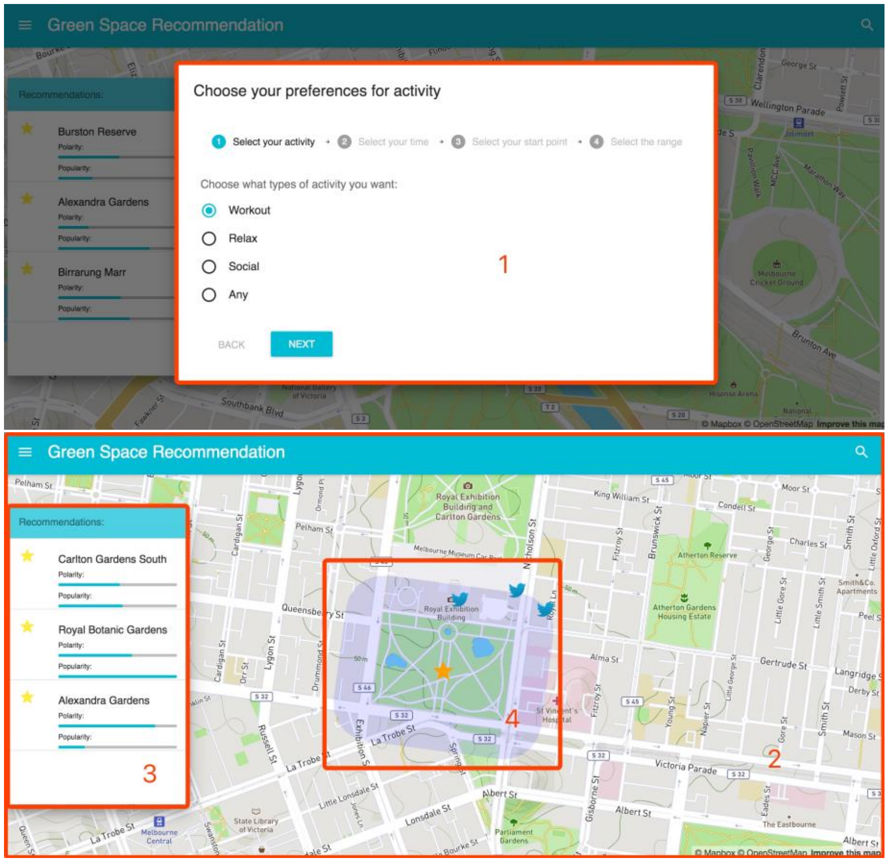


Figure 5.12: Our sentiment/activity-aware recommendation system, comprising: (1) user preference solicitation; (2) general map layout; (3) top three recommended green space; and (4) outline of recommended green space. Retrieved from (Wang et al., 2018).

8. General Discussion

In this section, we first highlight the main findings of our study, discuss some implications of these findings and describe future research directions.

8.1. Summary of Main Findings

Our main findings of how green spaces affect user sentiment are:

- RQ1: In general, tweets in green spaces are more positive and less negative than those in urban areas. When we examine these changes in terms of specific emotions, green spaces exhibit higher levels of joy, anticipation and trust (positive emotions), and lower levels of anger and fear (negative emotions), compared to urban areas.

- RQ2: While green spaces are generally more positive than urban areas, this varies by the season the tweet was posted. We observe that green spaces display higher polarity (more positive) than urban areas across the four seasons, with the size of this effect greater in warmer seasons (spring and summer) and smaller in colder seasons.

- RQ2: Breaking down our analysis in terms of hours and days, the results show sentiment changes that likely reflect the general lifestyle of users. For example, sentiment polarity is the lowest at the end of a work day (early evening) before gradually increasing through the evening after work. Similarly, sentiments are more positive during weekends than weekdays, with green spaces being more positive than urban areas across all days.

- RQ3: Our grid-based analysis shows that areas containing major transport-related infrastructures and residential areas are more likely to show negative sentiments, while almost all areas with green spaces exhibit positive sentiments (with the exception of an area that contained both a green space and a hospital).

- RQ3: Examining urban tweets, we find a correlation between the sentiment polarity of urban tweets and its distance to the nearest green space. The results show a significant negative correlation between negative tweets in urban areas and distance to green spaces but no significant correlation for positive tweets.

- RQ4: Our activity analysis shows that popular activities in larger parks are Food, Drinks and Events, and all park-related activities evoke positive sentiments, except the Education activity that is slightly negative.

8.2. Implications and Future Directions

These findings have some important implications for urban planning authorities (Zeile et al., 2015; Hartig and Kahn, 2016; Schetke et al., 2016) and smart city applications (Ahlers et al., 2016; Lytras and Visvizi, 2018). They add to the body of research on the benefits of green spaces, relevant for policies aiming to improve well-being outcomes through urban greening interventions; people express more positive emotions and less negative emotions in green spaces or in close proximity to one. In Melbourne (a large city in the Southern hemisphere), this effect is particularly notable in warmer months and on weekends. At some times of the year, e.g., autumn, more negative sentiment is expressed in parks than in urban areas. Further research could explore whether these seasonal changes can be mitigated (e.g. negative sentiment could be related to mess from falling leaves, which could be mitigated through additional maintenance), or whether park use can be promoted at optimal times.

In addition to implications for urban planning, our findings also have implications for the general recommendation of tour itineraries or Points-of Interest (POIs) (Taylor et al., 2018; Wang et al., 2016; Becker et al., 2015; Lim et al., 2019), particularly those that emphasize on the enjoyability and happiness of such tours (Quercia et al., 2014). To increase the enjoyability of tours, existing tour recommendation systems can incorporate a preference for POIs that are located in or near green spaces, as our findings show that these areas benefit from more positive and less negative sentiments. In addition, our observation of how different time periods affect user sentiments can be used to make context-aware tour recommendations that also consider the time or season when a tour itinerary is scheduled to commence.

This work can also be extended in several directions. One research direction is to examine the green space and urban effects in terms of other aspects, such as more specific categorization of green spaces (amount and types of foliage cover, species of trees and flowers), different types of urban areas (industrial, commercial, residential, entertainment) and user demographics (gender, age group, occupation) (Markevych et al., 2017). While our work focuses mainly on the text used in tweets, future work can utilize other media types, such as pictures and videos, and employ image recognition techniques alongside sentiment analysis on photo-sharing sites, similar to the studies on pet ownership and alcohol consumption using Instagram (Wu et al., 2016; Pang et al., 2015).

9. Conclusion

In this chapter, we studied the effects of green spaces on user sentiments based on digital traces left by Twitter users in the form of geo-tagged tweets and presented our main findings in Section 8. We utilized a big data driven approach to understand how green spaces are related to user sentiments across different time periods and spatial areas. In contrast to earlier works that utilizes surveys, questionnaires and case studies, our approach utilizes a large amount of Twitter data which can be easily collected and is neither intrusive nor time-consuming for the users (as the tweets are publicly available). These properties allow an unprecedented capacity for fine-grained analysis, such as capturing all green spaces at once, studying local effects, size effects, time effects, and proximity effects, thus also allowing to identify gaps. Moreover, our study methodology can be easily extended to examine other research questions, and thus this type of analysis is relevant for social researchers and psychologists who are currently using independent studies and traditional methods. For example, instead of administering surveys to understand how a specific crisis or natural disaster affects people's emotional well-being, we can perform sentiment analysis on a large amount of tweets that are posted in close proximity to the natural disaster or by users residing near the natural disaster.

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