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Racism in tourism reviews

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ABSTRACT

Racism is increasingly recognised as a key driver of unfair inequalities in power, resources and opportunities across racial groups. A comprehensive understanding of racism is beneficial to activist groups, policymakers and governments. Traditional approaches, such as surveys and interviews, are usually time-consuming and inefficient in capturing the occurrence of large-scale racism. In this study, we utilise routinely collected data available on tourism websites to assess self-reported racism in the tourism domain. We present a data acquisition procedure that collects racism-related reviews from the Internet at the global scale and then utilise statistics and natural language processing techniques to analyse and explore racism in terms of its tendency, distribution, semantics and characteristics. The effectiveness of the proposed method is demonstrated in a case study, in which we acquire racism-related data at the global scale and validate the impact of racial discrimination on tourists' experience.

1. Introduction

Racism is a social phenomenon that should not be ignored. It is a key factor that leads to unfair and avoidable inequalities in power, resources and opportunities across racial or ethnic groups (Berman & Paradies, 2010). This claim is reflected not only by increasing political attention but also by growing media coverage (Rodrigues, Niemann, & Paradies, 2019). Racism has various manifestations. Thus, it has been studied as a concept (i.e. beliefs, ideologies or worldviews) and as an action (i.e. forms of racial discrimination, such as offensive language or racist practices) (Paradies, 2016; Priest & Williams, 2017). Racism research is inherently multidisciplinary and has been the focus of research in humanities (Levy, 2017), social sciences (Henricks, 2015), cultural studies (Seikkula, 2019), economics (Lane, 2016), and law (Hirsh & Cha, 2018), among others.

With the development of the Internet, especially the rise of social networks, assumed anonymity and digital freedom of speech encourage people to freely disclose their racist ideologies or adopt an aggressive online behaviour with limited consequences. In today's digital era, racism has become common and virulent on the Internet. It has also drawn much research attention in various fields, from engineering and technical science to psychology and social sciences (Jakubowicz et al., 2017; Bliuc, Faulkner, & Jakubowicz, 2018; Fortuna & Nunes, 2018).

Fortuna & Nunes (2018) surveyed the automatic detection of hate speech, provided a unifying definition of hate speech and discussed the main techniques used in this field. They reviewed existing studies and found that nearly 42% focus on racism, while others consider general hate speech, sexism and anti-Semitism nationality (Fortuna & Nunes, 2018). Many researchers formalised the detection of online racism as a text classification task. They applied artificial intelligence (AI) techniques, such as deep learning, support vector machine (SVM), naïve Bayes classifier, logistic regression and decision trees, to handle this problem (Burnap & Williams, 2016; Davidson, Warmsley, Macy, & Weber, 2017; (Corazza et al., 2018); Huang, Zhang, Cheng, Li, & Li, 2018; Philander & Zhong, 2016).

Despite existing efforts in this area, attaining a comprehensive understanding on the worldwide situation of racism remains a challenge owing to limitations in data acquisition and data coverage. In relation to data acquisition, efficiently acquiring sufficient data on the nature, manifestations and prevalence of racism is important. Some institutes,

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such as Johnson Centre, investigated racism and discrimination via phone surveys of sampled residents.[1] Other research was conducted by searching scientific databases, using search engines to find target websites or personally contacting experts (Truong et al., 2013). These existing approaches are usually labour-intensive, time-consuming, infrequent and limited in the volumes of data acquired. Pertaining to data coverage, many recent studies on hate speech detection have attempted to collect data on various social network accounts self-classified as racists (Saleem, Dillon, Benesch, & Ruths, 2017; Huang, Zhang, Cheng, Li, & Li, 2018; Zimmerman, Fox, & Kruschwitz, 2018). Although obtaining racism data through these methods is relatively straightforward, the data coverage is limited to specific regions and/or groups.

Tourism is recognised as an important part of wider social, economic, political, ecological and cultural processes (Cole & Morgan, 2010). Along with globalisation and economic growth, tourism is frequently believed to be one of the fastest growing industries in the world (Cole & Morgan, 2010). According to the United Nations World Tourism Organisation (UNWTO 2019), the number of international tourists reached 1.4 billion in 2019. The development of tourism crosses geographical boundaries and promotes communications across racial, ethnic and cultural differences. This characteristic increases the possibility of exposing racial relations to some extent and opens a window to gaining a better understanding of racism reality around the world.

Advances in Internet technology have led to many online tourism communities, such as TripAdvisor, Airbnb, Booking and Yelp, in which tourists can obtain information on accommodations, dining and tours. Moreover, tourists can publicly post reviews and freely share their first-hand travel experiences. Therefore, public reviews have become a rich and valuable data source which has attracted the attention of many researchers from various fields. Most of these studies benefitted from text analytics of online tourist reviews because tourism websites allow data acquisition at a large scale. For example, some prior studies addressed tourists' assessments or expectations of tourism services (Liu, Law, Rong, Li, & Hall, 2013; Sirakaya-Turk, Nyaupane, & Uysal, 2014; Jeong, Han, & Mankad, 2016); movement and activity patterns (Hasnat, 2018; Talpur & Zhang, 2018; Vu, Li, Law, & Zhang, 2018); and preferences in destinations, dining and hotels (Li, Law, Vu, & Rong, 2013; Maeda, Yoshida, Toriumi, & Ohashi, 2018; Vu, Li, Law, & Zhang, 2019).

Tourists from various backgrounds share and post their first-hand, racist-related experience on a tourism platform. This action provides a unique opportunity for researchers to effectively acquire quality data related to racism. Moreover, these tourism reviews come from different parts of the world, thereby helping alleviate existing limitations on data coverage. In the current work, we firstly present a data acquisition procedure that acquires racism-related reviews from the Internet at the global scale. We then conduct a quantitative analysis to examine the existence of racism globally. Finally, we undertake a content- and sentiment-based analysis to further understand the racism experiences of tourists.

To our knowledge, tourism data have rarely been used in existing literature, if ever, to analyse and assess racism at the global scale, thus providing the niche for this study to contribute to extant knowledge in this field of inquiry. This method and the associated findings may benefit the tourism sector, activist groups, policymakers and governments. This study will also release a publicly available data source with a large sample size for future research on racism.

The rest of the paper is organised as follows. Section 2 reviews existing work on racism detection and tourism reviews. Section 3 presents the methods for extracting, processing and analysing racism in tourist reviews. Section 4 demonstrates the effectiveness of this approach through a case study. Finally, Section 5 concludes our work with implications and future research directions.

2. Related work

2.1. Research on racism towards tourists

Dillette, Benjamin, & Carpenter (2019) conducted research on how Black tourists experience travel by analysing over 300 tweets using the trending hashtag #TravelingWhileBlack. This work identified occurrences of racism, awareness of being Black while travelling and experiences travelling while Black, all of which will contribute to creating a more just society by revealing the experiential knowledge of Black travellers. However, this method implicitly excluded tourists who do not use hashtags to share their opinions and those who do not use Twitter (Dillette, Benjamin, & Carpenter, 2019). Furthermore, the data did not have the demographic information of the participants and the geographic information of tourist destinations, a deficiency which precludes a more comprehensive understanding of Black travellers' experience (Dillette, Benjamin, & Carpenter, 2019).

International students, as educational tourists, have increased with globalisation. Muñoz, Pineda, & Radics (2017) reported that more than five million international students have enrolled overseas for tertiary education, and this figure is expected to reach 8 million by 2025. The rapid growth of the international student market has also stimulated local businesses and the tourism industry and brought potential economic benefits (Gardiner & Kwek, 2017). However, international students may experience racism and other forms of discrimination within the context of international cooperation and exchange. Marginson, Nyland, Sawir, & Forbes-Mewett (2010) proposed that racism is one of the leading factors contributing to international student dissatisfaction.

Some existing literature and investigations focused on racial discrimination towards international students. Harwood, Mendenhall, Lee, Riopelle, & Huntt (2018) from University of Illinois conducted an online e-mail survey with more than 4800 citizens or permanent resident students of color in the United States. Their study revealed that many students of different skin colours have experienced racial hostility and exclusion in their daily routines or been treated as second-class citizens. Some students resisted, but also faced opposition (Harwood, Mendenhall, Lee, Riopelle, & Huntt, 2018). Harwood et al. (2018) demonstrated that a racially harmonious campus is imaginary. Macionis, Walters, & Kwok (2019) held four group interviews with Singaporean students who were studying at an Australian university. Several participants recounted their negative experiences in which they were recipients of racist comments or actions. The participants encountered racism in a variety of ways, from subtle words to blatant discrimination (Macionis, Walters, & Kwok, 2019). Although Australians have a positive image as friendly, independent, laidback, and have good work–life balance, this image was negatively affected by racism encounters. Macionis et al. (2019) likewise found that, compared with Indians and Malays, Chinese participants have encountered the greatest amount of racism. This finding is consistent with previous literature stating that Australians generally show less tolerance for Asian compared to other cultural groups (Dunn, Forrest, Burnley, & McDonald, 2004). Lee (2015) interviewed 24 students from 15 countries in a university in the south-western region of the United States. The authors found that international students from Asia, Africa, Latin America and the Middle East are more likely to experience discrimination than those from Europe, Canada or Australia, who were generally more satisfied with their studies in the United States. Other research findings also provide evidence of racism against non-European students (Lee & Rice, 2007), particularly international students from East Asian, African and Middle Eastern countries (Hanassab, 2006; Gareis, 2012). Brown & Jones (2013) examined the experiences of international students studying in England and found that nearly one-third of the students experienced some form of racism.

Racism is a key offensive behaviour towards foreigners, for whom

[1] http://johnsoncenter.org/resources/community-data/voicegr2014/racism-discrimination/.

Table 1
Review information.

Metadata	Description
Venue	Venue of the review (e.g. a hotel, restaurant or attraction)
Address	Address of the hotel, restaurant or attraction
User's location	Geographic information in the user's profile
Date	Date of the experience
Review title	Title of the review
Review text	Content of the review

Table 2
Dataset.

	Hotel	Restaurant	Attraction	Total
Counts	451	991	641	2081
Number of Reviews	623	1644	2287	4554
Percentage of Reviews	13.68%	36.10%	50.22%	100%

this creates a negative impression of the host country (Brown & Jones, 2013). In these studies on racism towards international students, online surveys and interviews were the commonly used methods. However, these methods suffered from the limited coverage of the target population and unpredictable information delay. Determining an approach to acquire data effectively and in a timely manner is challenging but valuable in seeking to overcome the above limitations and providing better insights into racism in the tourism domain.

2.2. Research on online racism detection

As a particular type of hate, racism has become a popular research topic in computer science and cyberspace. This section reviews studies on hate speech and racism.

2.2.1. Surveys on hate speech detection

Two survey articles on hate speech detection were published recently (i.e. Schmidt & Wiegand, 2017; Fortuna & Nunes, 2018), and both provided a comprehensive overview of the automatic detection of hate speech. Schmidt & Wiegand (2017) initially presented related terminologies for understanding hate speech used in the natural language processing (NLP) community, such as abusive messages, hostile messages or flames, cyberbullying, insults, profanity, offensive language, vulgar language and profanity-related offensive content. They then analysed those features used to differentiate hate speech from harmless utterance and summarised the hate speech detection methods. Fortuna & Nunes (2018) provided a unifying definition of hate speech as language that diminishes or attacks, thereby inciting violence or hate against certain groups because of their specific characteristics, such as national or ethnic origin, religion, descent and physical appearance. To understand this complicated concept, the authors compared hate speech with hate, cyberbullying, abusive language, discrimination, profanity and other related concepts. Moreover, they conducted a systematic literature review and presented the analysis results of these documents from various aspects, such as the area of knowledge, year of the document, publication venue, keywords in the document and algorithms used (Fortuna & Nunes, 2018). Their findings indicated that building a machine learning model for classifying hate speech is the most common method, and SVM, random forests and decision trees are the most popular algorithms.

2.2.2. Algorithms of hate speech detection

In terms of AI approaches to hate speech detection, Pitsilis, Ramampiaro, & Langseth (2018) developed a recurrent neural network for hateful content classification which utilised the features derived from the behavioural data of users. Zimmerman, Fox, & Kruschwitz (2018) proposed an ensemble method adapted for usage with neural networks and found that this method classified hate speech thoroughly. Badjatiya, Gupta, Gupta, & Varma (2017) proposed multiple deep learning architectures to learn semantic word embedding in tackling this problem; these multiple classifiers included logistic regression, random forest, SVM, gradient boosted decision trees and deep neural networks. Other algorithms associated with neural networks are adopted in Graves (2013), Del Vigna & Cimino (2017), Biere & Bhulai (2017), and Corazza et al. (2018). Several classical machine learning models are also often used to address this research problem. SVM is the most common and frequently used algorithm in the works of Burnap & Williams (2014), Burnap & Williams, 2016, Tulkens, Hilte, Lodewyckx, Verhoeven, &

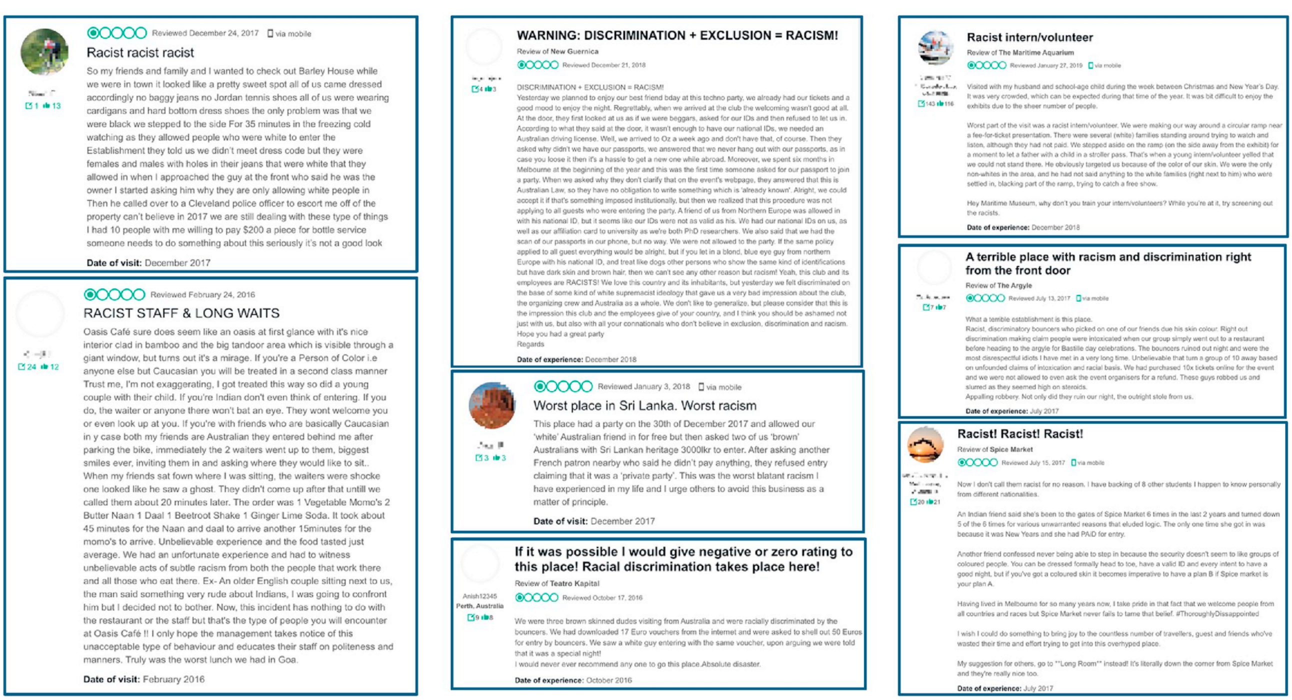

Fig. 1. Occurrences of racism in tourism reviews.

Fig. 2. Trends over time on reviews pertaining to racism.

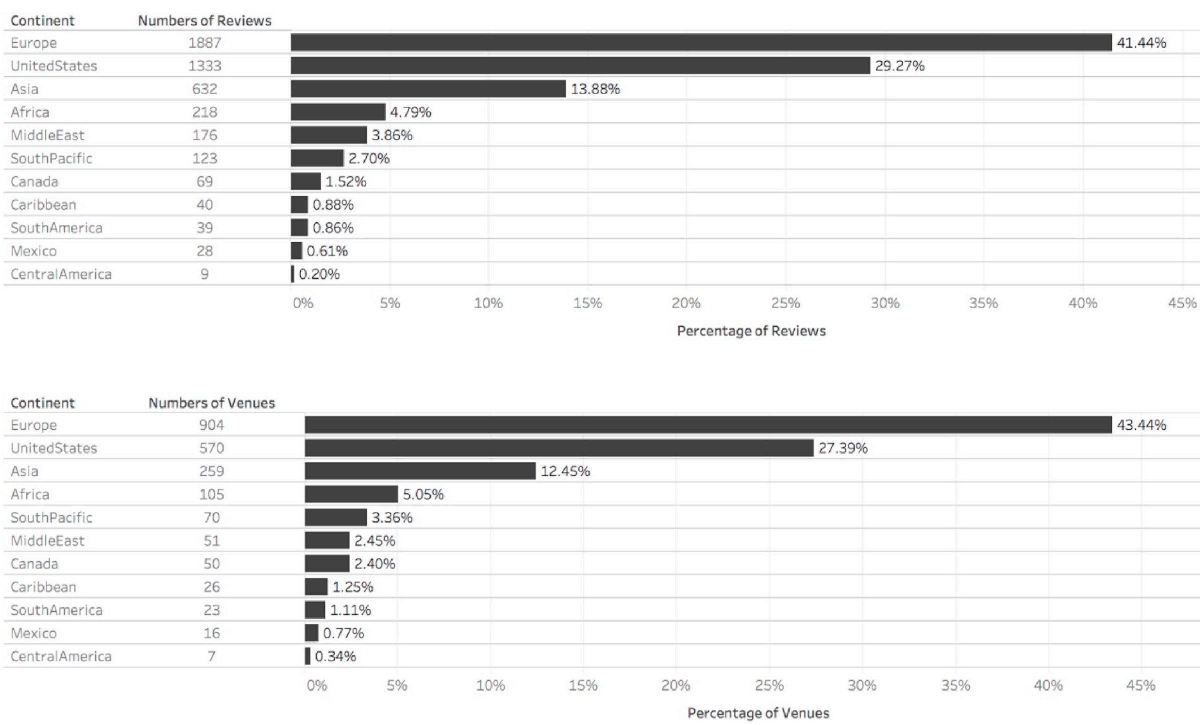

Fig. 3. Distribution of racism in reviews by key regions.

Daelemans (2016), Davidson, Warmsley, Macy, & Weber (2017), and Gupta & Waseem (2017). Huang et al. (2018) selected racist tweets from Twitter accounts self-classified as racists and applied the naïve Bayes classifier to identify racist tweets and accounts. Burnap & Williams (2016) employed random forest and decision tree algorithms to detect hateful content propagated via the World Wide Web. Additionally, Tulkens et al. (2016) detected racism on the basis of a dictionary that combines Linguistic Inquiry and Word Count (LIWC) dictionary for Dutch with another one containing words that specifically relate to racist discourses.

Overall, many existing studies formalised hate speech detection as a text classification task and attempted to adopt various AI classification algorithms to detect online hate speech.

2.2.3. *Natural language processing techniques in review processing*

In recent years, NLP techniques have enabled the effective identification of the right features for text classification. NLP has been adopted widely in text processing tasks, including the automatic detection of hate speech (Graves, 2013; Gitari, Zuping, Damien, & Long, 2015; Davidson, Warmsley, Macy, & Weber, 2017; Del Vigna & Cimino, 2017; Saleem,

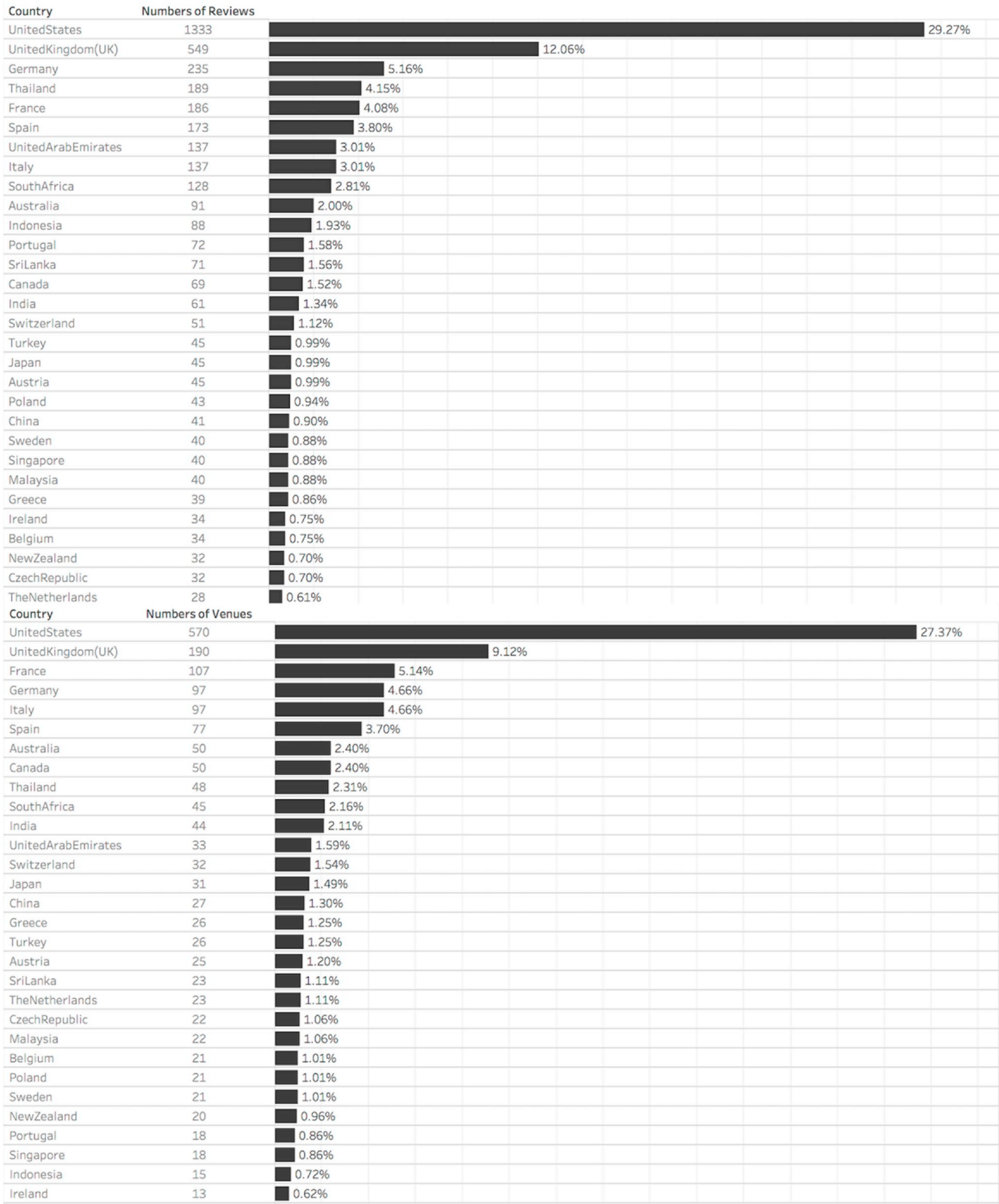

Fig. 4. Distribution of racism-related reviews by country.

Dillon, Benesch, & Ruths, 2017; Thomas, Mehdad, Nobata, Chang, & Tetreault, 2017; Biere & Bhulai, 2017). N-gram incorporates the context of each word at certain degrees and has become one of the most used approaches in processing hate text (Burnap & Williams, 2014, Burnap & Williams, 2016; Davidson, Warmsley, Macy, & Weber, 2017; Del Vigna & Cimino, 2017; Thomas, Mehdad, Nobata, Chang, & Tetreault, 2017). Part-of-speech technique has also been used to detect hate speech because it can identify the category of a word in a sentence, such as adjective, noun and verb base form, and improve the importance of key terms (Davidson, Warmsley, Macy, & Weber, 2017; Del Vigna & Cimino, 2017; Thomas, Mehdad, Nobata, Chang, & Tetreault, 2017). Several authors (e.g. Graves, 2013; Djuric et al., 2015; Del Vigna & Cimino, 2017) used the Word2vec method to classify comments on social media. Sentiment has been used as an important feature for hate speech

Fig. 5. Country coverage of racism-related reviews.

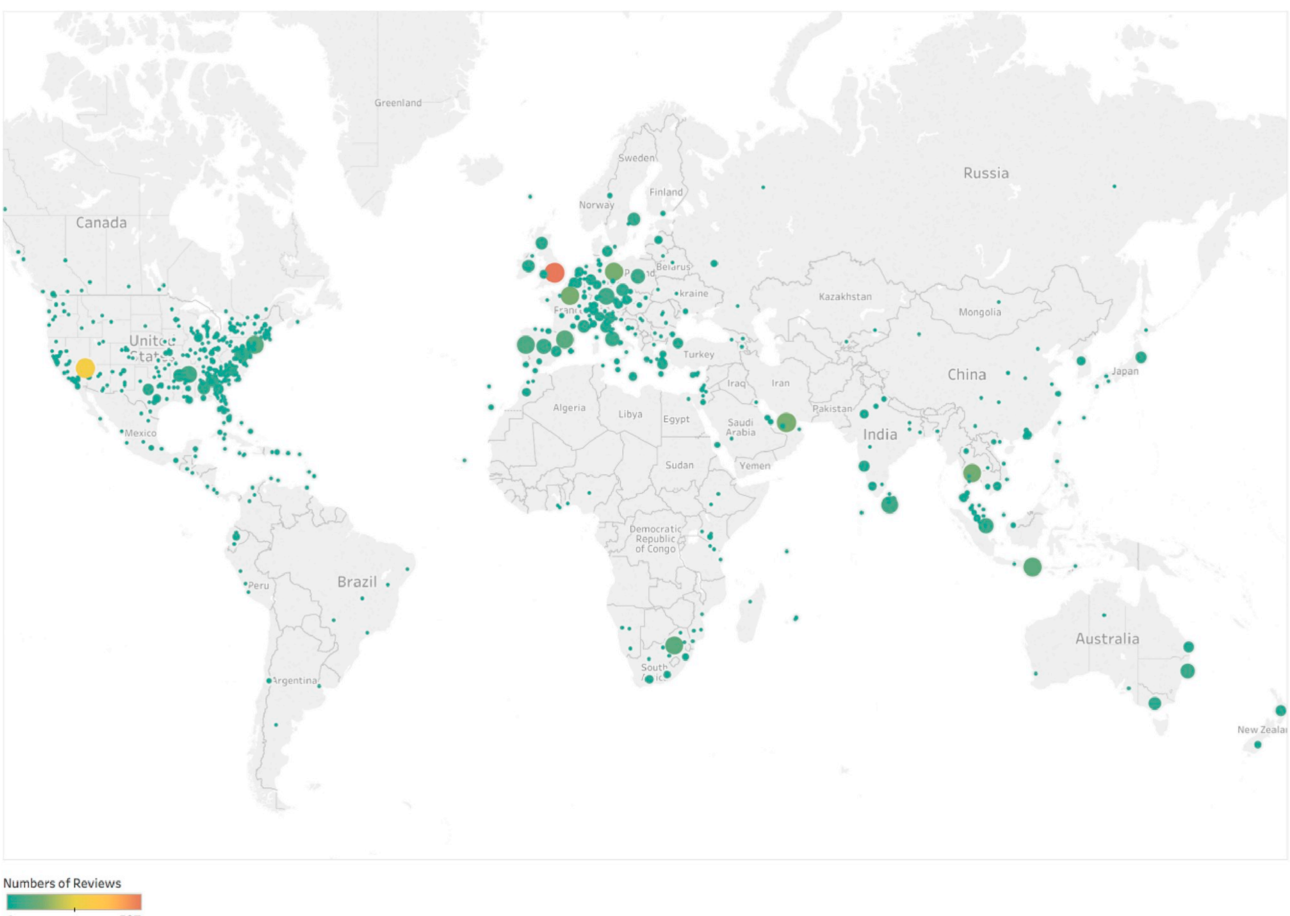

Fig. 6. Density map of racism distribution.

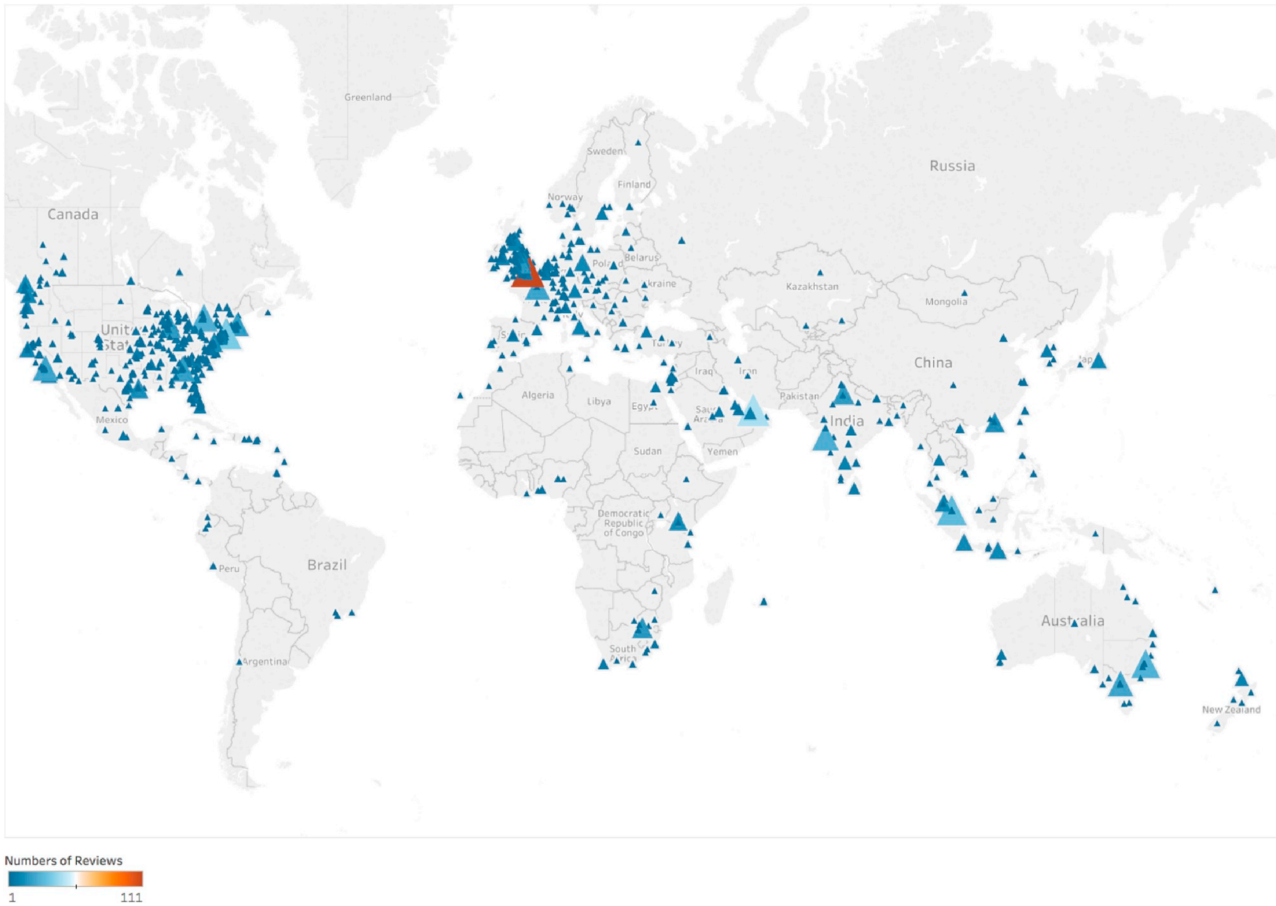

Fig. 7. Density map of reviewers' location.

detection because hate speech has a negative polarity (Gitari, Zuping, Damien, & Long, 2015; Davidson, Warmsley, Macy, & Weber, 2017; Del Vigna & Cimino, 2017). Researchers usually combine these features to improve the performance of hate speech detection.

2.2.4. *Datasets of racism studies*

Social media is the focus of the datasets used in previous works. Twitter is the most commonly used source of dataset (Burnap & Williams, 2016; Silva, Mondal, Correa, Benevenuto, & Weber, 2016; Waseem & Hovy, 2016; Badjatiya, Gupta, Gupta, & Varma, 2017; Davidson, Warmsley, Macy, & Weber, 2017; Gupta & Waseem, 2017; Biere & Bhulai, 2017; (Corazza et al., 2018); Pitsilis, Ramampiaro, & Langseth, 2018; Zimmerman, Fox, & Kruschwitz, 2018), followed by Facebook (Tulkens, Hilte, Lodewyckx, Verhoeven, & Daelemans, 2016; Del Vigna & Cimino, 2017; Corazza et al., 2018), Yahoo (Thomas, Mehdad, Nobata, Chang, & Tetreault, 2017) and other social networking sites, such as Reddit (Saleem et al., 2017) and Whisper (Silva et al., 2016). Data acquisition from social networking sites is popular because of their user-friendly application programming interfaces (APIs) and a vast number of users. However, most of these datasets are not available publicly. Moreover, a small part of data from one social networking site may be enough for hate speech detection but insufficient to understand racial reality at a global scale.

2.3. *Research on online tourism reviews*

Data from tourism websites enable the analysis of tourists' preferences in various respects, such as restaurants, hotels and tourism sites. Vu et al. (2019) analysed the dining behaviours of tourists by using large-scale restaurant online reviews from TripAdvisor, which presents comprehensive insights into the dining preferences of tourists. Yu Zhang, Ji, Wang, & Chen (2017) also used restaurant reviews from TripAdvisor to build a decision model that can help tourists select restaurants. Gan, H. Ferns, Yu, & Jin (2016) collected reviews on Yelp to analyse the structure and sentiment of online restaurant reviews. Maeda et al. (2018) developed a method to compare different preferences of tourist destinations between foreign and domestic tourists. They verified and demonstrated this method in a case study on Japan using a dataset from Twitter. Hausmann et al. (2018) compared tourists' preferences for nature-based experiences from a traditional survey with observed preferences assessed from Instagram and Flickr. They found no significant difference between the results as stated in the survey and the results revealed by analysis of Instagram. Examination of Flickr found that tourists have a preference for less-charismatic biodiversity that was not found using the traditional survey (Hausmann et al., 2018). Thus, social media content can be regarded as an efficient way to explore preferences.

Tourist destinations and routes were likewise studied on the basis of data collected from social networking sites. Hasnat et al. (2018) studied the destination choices of tourists by gathering and analysing location-based data from Twitter. Zhou, Xu, & Kimmons (2015) automated the detection of tourist destinations according to the spatial and temporal features of geotagged photo data from Flickr. García-Palomares, Gutiérrez, & Mínguez (2015) identified the main tourist hot spots in eight major European cities by analysing spatial distribution patterns of geotagged photographs from social networking sites.

Tourists' behaviour and mobility also draw attention as popular research topics. Talpur & Zhang (2018) used social media data to capture information regarding tourist sequential activities and identified insights into tourist movement pattern by using advanced data mining

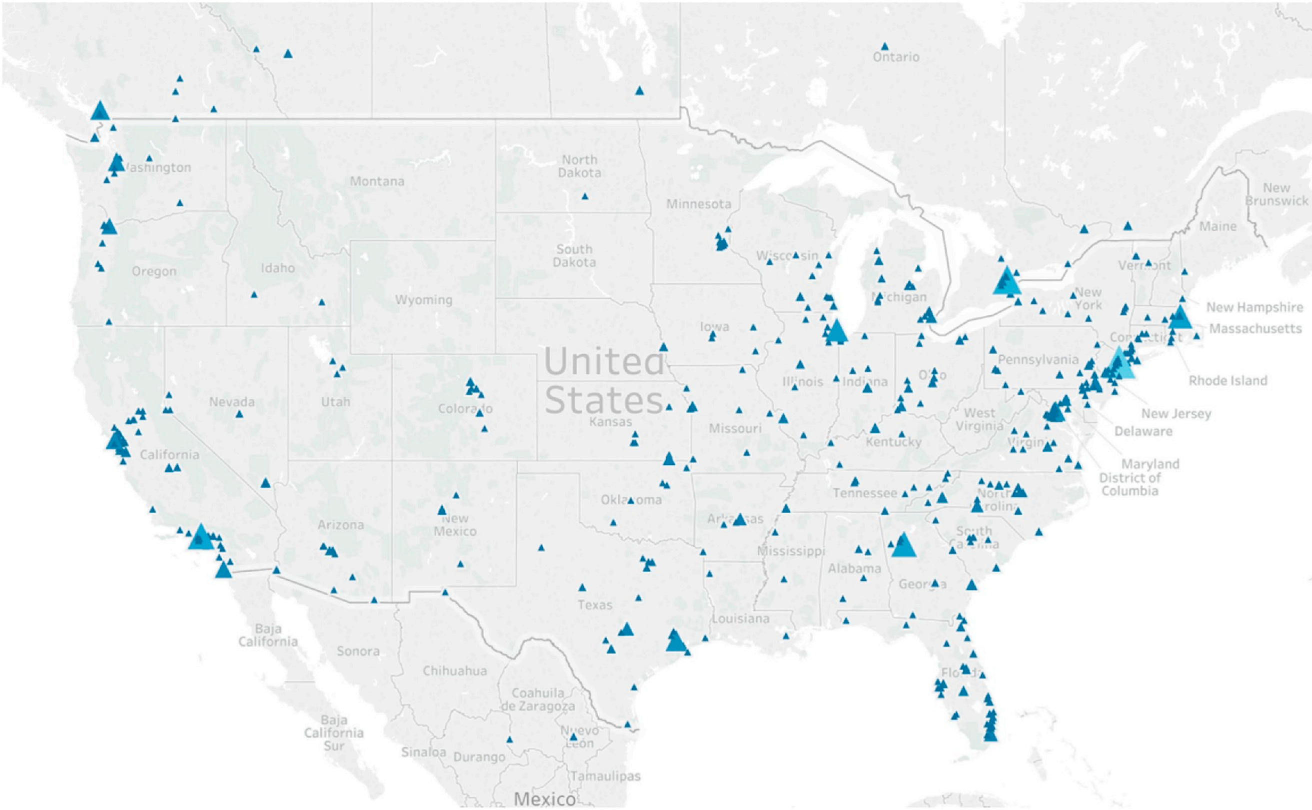

Fig. 8. Density map of reviewers' location in the United States.

techniques. Vu et al. (2018) used social media to capture the movements and travel patterns of tourists at a large scale and analysed their activity on inbound tourism in Hong Kong. Miah, Vu, Gammack, & McGrath (2017) took Melbourne, Australia, as a representative case, used geotagged photos posted by travellers to social networking sites–Flickr, and predicted travellers' behaviour patterns at specific destinations. Vu, Li, Law, & Ye (2015) exploited the geotagged photos available on a social networking site and analysed the movement trajectories of tourists with different profiles. The effectiveness of the proposed method was demonstrated through a case study on Hong Kong inbound tourism (Vu et al., 2015).

Several researchers recently attempted to evaluate tourists' sentiments. Philander & Zhong (2016) demonstrated a method for understanding tourists' sentiment for hospitality. Zhu & Newsam (2016) developed an emotion classifier to detect the sentiment conveyed in geotagged photos from Flickr.

Various tourism studies were conducted using data from mainstream social networking sites, such as TripAdvisor, Yelp, Flickr and Twitter. Data from these platforms bring new perspectives and opportunities to tourism research. The above research advanced the literature on tourists' preferences, destinations, behaviour and sentiments by analysing online tourism reviews and providing better insights for different stakeholders, who typically include tourism practitioners, tour agencies and tourists themselves.

3. Methodology

This section details how online tourism reviews can be used to assess self-reported racism in the tourism domain at a global scale. Firstly, it outlines how the racism reviews are collected for accurate and objective analysis. Secondly, it describes the required data pre-processing steps prior to analysis. Finally, it introduces a series of exploratory analyses to provide comprehensive insights into global experiences of racism in the tourism and hospitality context.

3.1. Data acquisition

A reliable and comprehensive dataset is the foundation of accurate insights into racism worldwide. This work collected experimental data from one of the world's largest travel websites.,It contains million of reviews and opinions on millions of accommodations, restaurants, airlines, cruises and experiences. It also covers the world's largest selection of travel listings. We selected this travel website as the data source for two reasons. On the one hand, as a global and social tourism platform, it provides a setting within which people from different religious and cultural backgrounds communicate with one another to the extent that racism is likely to be exposed. Using reviews, Vu et al. (2019) explored the dining preferences of tourists from various nationalities and cultures. On the other hand, it enables travellers to openly share experiences from their trips and freely express their opinions, thereby readily allowing the identification of user-generated reports of racism experiences.

Web-scraping is a convenient technology that enables researchers to easily collect reviews from the target website. We needed to find link patterns for sufficient reviews on different web pages and use web-scraping software to crawl into those links and glean the webpages through navigating and extracting content automatically. In this work, the data were expected to cover global reviews because we wanted to explore racism at the global scale. If we only crawled several websites for thousands of reviews, only a few racism comments might be detected amongst the collected comments. However, crawling all reviews posted on the travel website is impractical, if not impossible, because it is time-consuming and breaches the website's policy. The travel website provides a search function to focus on specific topics of interest. Therefore, in this work, we initially selected a list of seeding keywords to filter the webpages containing racism-related reviews. Seeding keywords, such as

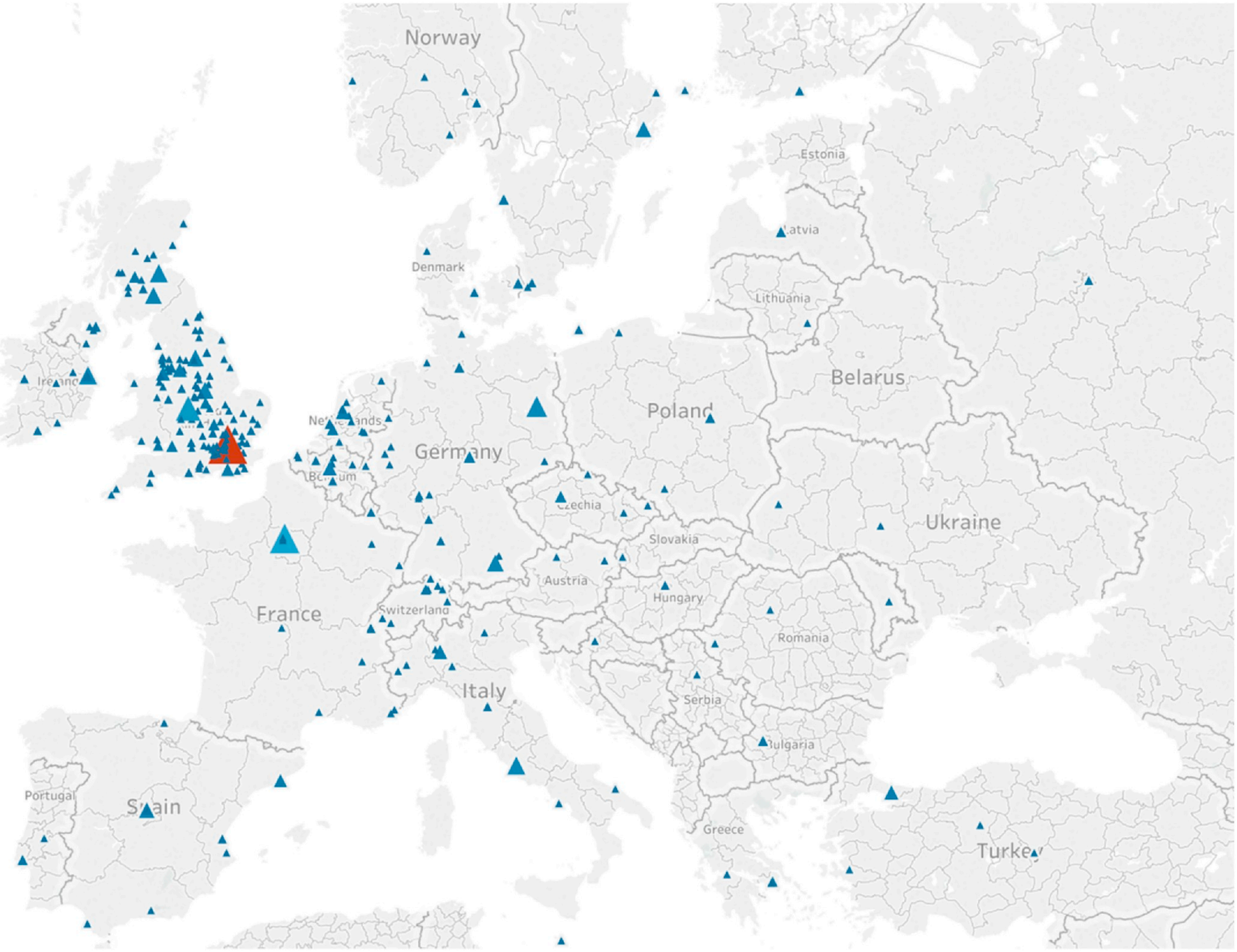

Fig. 9. Density map of reviewers' location in Europe.

'racist', 'racism', 'racial', 'nigger' and 'chink', were chosen from Wikipedia.[2] We crawled the webpages for reviews related to these seeding keywords. Thus, a comprehensive racism dataset could be obtained as a reference for further analysis.

A typical review consisted of the venue, address, user's location, date, review title and review text (Table 1). Amongst these attributes, venue indicates the locations where travel experiences happened: a hotel, restaurant or attraction. Address declares the specific geographical information of the venue, which is a key factor allowing the analysis of the spatial distribution of racism. User's location can be used to determine the place of origin and nationality of tourists. Date provides the time at which the comment was made. Review title is the headline of the comment, and review text is the comment that describes their experiences and feelings.

3.2. Data pre-processing

3.2.1. Annotations

After data crawling, data quality was enhanced via data cleaning. Human annotation was essential because the presence of the word 'racist' or other related seeding keywords in the comments did not guarantee racism as a topic of the review. We asked annotators to assess if messages convey any racism. Annotators considered the words and phrases appearing in the given comment and the context in which they were used, thereby improving the accuracy of the result.

In this manual annotation task, reviews were annotated at the comment level. Each review was annotated by three or more people, with the majority decision used as the final annotation. Reviews that no one considered racist were omitted.

3.2.2. Location processing

Location processing has two aspects, namely address and user's location. Address gives information about the location of the racial phenomena and provides the detailed address, including the specific location, city, country and continent. Such data allowed us to explore the geographic distribution of racism. User's location (e. g. New Delhi, India) indicates the reviewer's origin and implies that users from that region have experienced racial discrimination to some extent.

To map and visualise the geographic distribution of racism, we converted the location information into a uniform format and implemented address resolution from locations to latitudes and longitudes via Google Geocoding API.[3] For instance, given a user-provided address, such as Abruzzo, Italy, Europe, Google Geocoding API can automatically identify and return 42.1920119 and 13.7289167 as its latitude and longitude coordinates, respectively.

[2] https://en.wikipedia.org/wiki/List_of_religious_slurs.

[3] http://developers.google.com/maps.

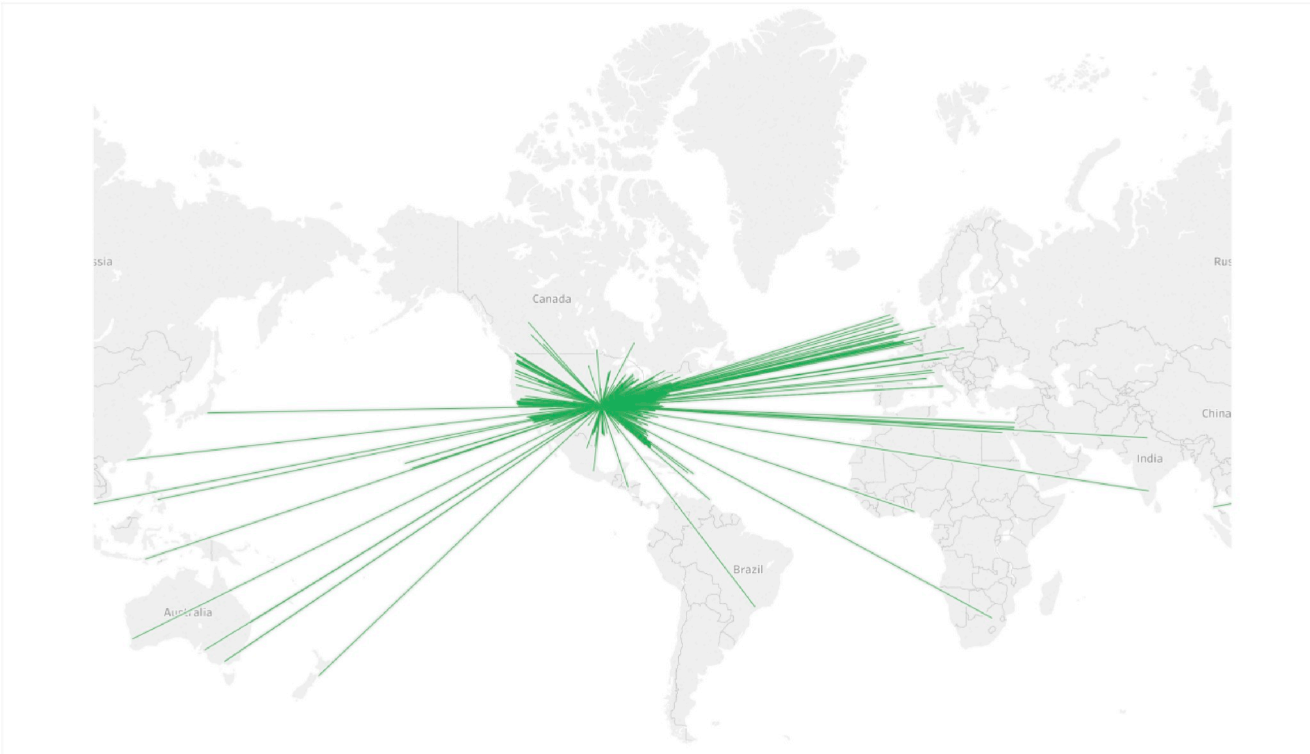

Fig. 10. Trajectory of tourists to the United States.

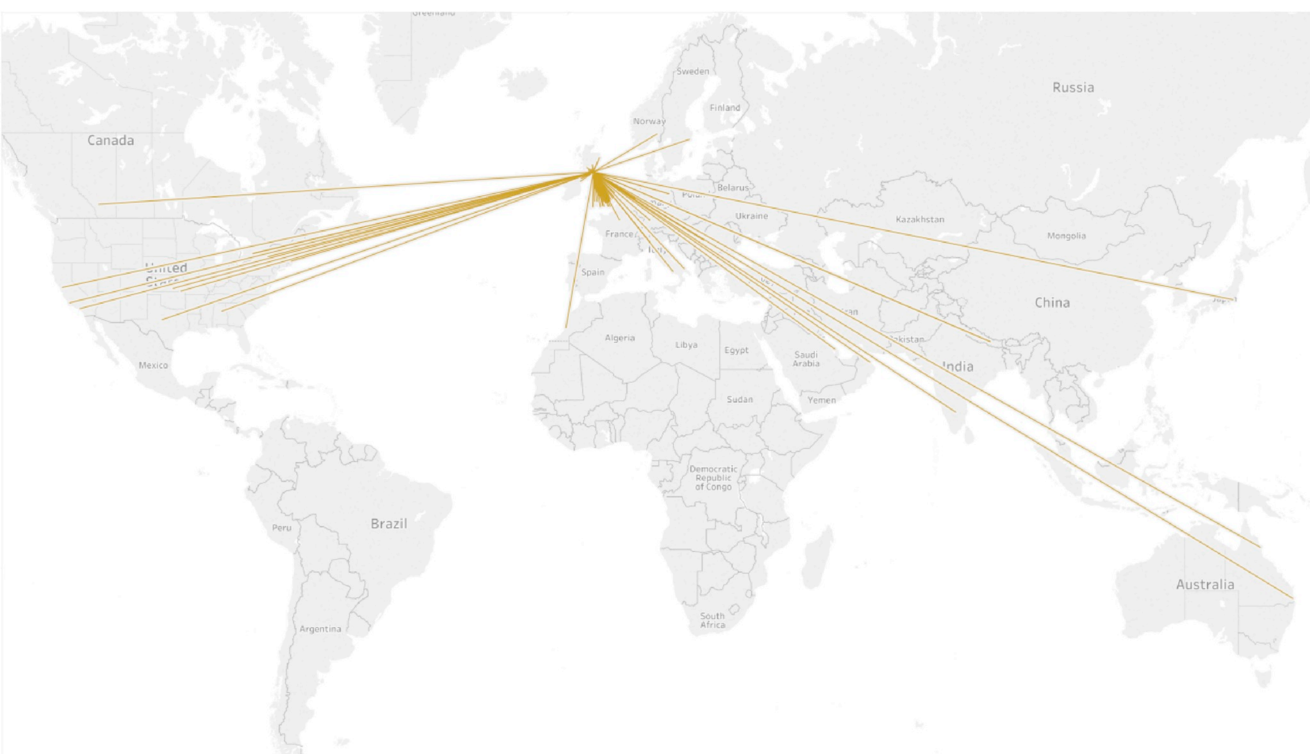

Fig. 11. Trajectory of tourists to the United Kingdom.

3.2.3. *Review text processing*

Data can be noisy because the comments from the Internet are contributed by reviewers with various backgrounds. Therefore, we firstly normalised these review texts. The main measures applied in practice include expanding the abbreviations and replacing some special characters, such as '*' and '#'. We then adopted numerous NLP techniques to process the textual comments. We mainly undertook this process using the Natural Language Toolkit (NLTK), which is a leading

Fig. 12. Word cloud for nouns.

Fig. 13. Word cloud for adjectives.

platform for building Python programs to work with human language data. Specifically, we split the text into tokens for analysis. These tokens could be paragraphs, sentences or individual words. This step is called tokenisation.

Consider the dataset R with T reviews, $R^T = \{r_1, r_2, ..., r_t\}$. For each review r_t, sentence tokenisation produces a list of sentences, and the sentences of all reviews are placed in a list $S^M = \{s_1, s_2, ..., s_m\}$. For each review r_t, word tokenisation produces a list of words. We processed all the reviews, removed duplicated words and saved them in a list $W^N = \{w_1, w_2, ..., w_n\}$.

After word tokenisation, the process of stemmers removes morphological affixes from words, leaving only the word stem. Stop-word removal deletes common English words, such as is, on and in. Finally, for our analysis in Section 3.3, we needed to discriminate words, such as nouns or adjectives, which could be achieved by part-of-speech tagging in NLTK. We ended up with two lists, namely the list of nouns and the list of adjectives, which are expressed as Eq. (3.1).

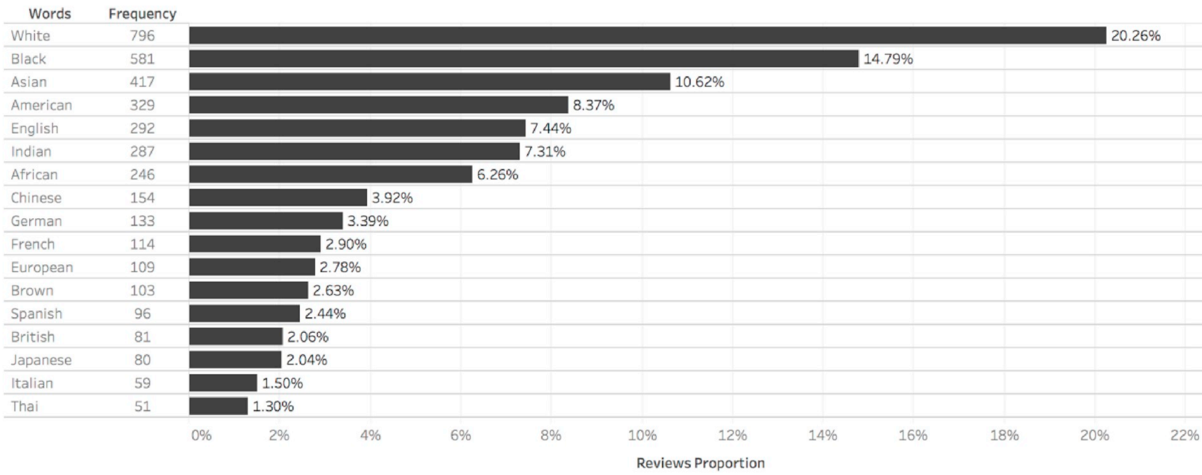

Fig. 14. Frequency ranking by country name.

Fig. 15. Word cloud for country name.

$$\begin{cases} Wnoun^{P} = \{\mathbf{w}_1, \mathbf{w}_2, \cdots, \mathbf{w}_p\} \\ Wadj^{Q} = \{\mathbf{w}_1, \mathbf{w}_2, \cdots, \mathbf{w}_q\} \end{cases} \quad (3.1)$$

3.3. Exploratory analysis

After pre-processing the data, we then conducted a series of analyses on racism in tourism research. The statistical analysis consisted of three aspects: the racism trend over time, the spatial distribution of racism-related events and the map of users' locations. Some NLP analyses attempted to explore the most commonly used words, semantics in reviews and sentiments for racism.

3.3.1. Temporal trend

The development over time is a basic analysis that counts reviews per year to indicate if online racist reviews are rising. Another important indicator is the number of venues, which indicates if racial inequality exists in more venues over the years.

3.3.2. Spatial distribution

Spatial distribution indicates the countries or areas where tourists have experienced racial inequality, thereby reflecting the global distribution of racism in tourism experiences. Address was used in this part, and it was transformed to latitude and longitude via Google Geocoding API. This processing is also helpful for data visualisation.

We assessed the number of racism-related reviews in each geographical area and venue (hotels/restaurants/attractions) included in this area. Both types of analyses help clarify the spatial pattern of racism in tourism. Moreover, we showed the results at multiple levels, namely continent, country and city.

3.3.3. Profile of reviewers

This study is not only concerned with the location of racism but also about who might suffer from such unfair treatment. Both aspects are important for a deep understanding of racism. In this section, we focused on the people who shared their racism-related experiences.

This case study was conducted by analysing the reviewers' home location, which relates to the user's location in Table 1. The user's location is visualised on a map to provide a quick and intuitive expression of the regions where people are likely to be treated differently. The trajectory of tourists from the starting address to the tourist destination was also mapped to identify the tourists' origin and the places where they are vulnerable to racism as well as explore the

Fig. 16. Word cloud of Hatebase vocabulary.

Table 3
Clusters of noun aspects.

Clusters of Noun Aspects	Numbers	Examples
Employee	79	diner, waiter, waitstaff, customer, manger, villager, eater, drinker, master and chef
Environmental Facilities	463	freezer, fridge, toaster, cushion, blanket, pillow, cloth, furniture, cardboard and armchair
View and Traffic	103	garden, backyard, fence, rent, ranch, jungle, mountain, bridge, highway and airplane
Area Name and Personnel Name	181	Colorado, Columbia, Boston, Washington, India, Florida, Mexico, Stephen, Josh and Kobe
Food	164	wonton, buffet, meal, homemade, beef, cheese, cucumber, mustard, alcohol and cocktail
Dress and Animals	78	dress, skirt, scarf, coat, pant, goose, bird, pigeon, rabbit and goat
Time	23	Saturday, Friday, Sunday, Wednesday, Thursday, March, April, December, November and yesterday
Mixture of Common Nouns	595	mail, notion, fact, everything, hope, forgot, dude, problem, affair, reason and muster

Table 4
Clusters of adjective aspects.

Clusters of Adjective Aspects	Numbers	Examples
Nationalities	92	Korean, Chinese, Viet, Bangkok, Indian, Indonesian, Malaysian, Lankan, Pakistani and Italian
Description of Emotion[6]	**155**	**rude, disappointed, letdown, abominable, disgraceful, deplorable, awful, unacceptable, unimpressed and offended**
Description of Goods	114	old, large, fresh, hot, strong, fast, tough, heavy, clean and full
Description of Food	65	tasty, delicious, sweet, goodness, mouthful, creamy, aromatic, flavour, spice and dessert
Description of Environmental Facilities	199	blue, spacious, comfortable, gorgeous, luxurious, modern, traditional, exquisite, fantastic and sensational
Description of Decorations	127	interior, exterior, wooded, plastic, flower, edible, wild, exotic, rough and displayed
Mixture of Common Adjectives	340	accessible, safe, expensive, labelled, whole, private, social, sudden, local and mobile

underlying relationships between them.

3.3.4. Reviews semantic analysis

Automatically identifying the semantic meaning of reviews was a challenging task due to the richness, diversity and intelligence of language text. To obtain further in-depth information on the semantic meaning, we analysed these reviews in various ways. Three methods are described in this section, namely the statistics of high-frequency words, the search of target words on the basis of a self-documenting dictionary and hate speech detection.

Firstly, high-frequency words are informative on the text topics. To find the most frequently used words from thousands of reviews, we could keep a tally for each word in all reviews or count the reviews containing the word. The latter was more representative than the former because our purpose was to have a systemic overview of the collected reviews. Moreover, we only focused on the nouns and adjectives, which are notional words.

As described in Section 3.2.3, the dataset R includes T review comments, $R^T = \{r_1, r_2, ..., r_t\}$. After pre-processing, we have the lists of nouns and adjectives expressed as Eq. (3.1). For each word w_p in $Wnoun^P$, the number of reviews that contain the word w_p was counted and noted as N_{w_p}, and the frequency was N_{w_p}/T. Finally, we obtained two frequency lists of all nouns and adjectives, which are noted as Eq. (3.2).

Table 5
Aspects of emotion description.

abominable	abusive	abysmal	aggressive	aloof
angry	annoyed	anxious	apologetic	appalled
apprehensive	arrogant	atrocious	awful	awful
bizarre	boisterous	chaotic	claustrophobic	clumsy
confusion	crappy	crowed	deceptive	deplorable
desperate	dirty	disappointed	discourteous	disgraceful
disgust	dislike	dismal	dismayed	dismissive
disregard	disrespectful	distract	dreadful	drown
dull	dumb	embarrassed	filthy	fooled
frantic	freak	furious	fuss	greasy
guilt	harsh	hesitant	horrendous	horrible
horrific	hungry	ignorant	impatient	impolite
inattentive	incompetent	indifferent	inept	insane
irrelevant	jealous	lackadaisical	lackluster	lame
lazy	letdown	limp	loud	lousy
messy	miserable	nasty	nervous	noisy
nonsense	obnoxious	offended	outrageous	overcharged
overheard	painful	particular	pasty	pathetic
picky	pitiful	pompous	poor	predictable
pretend	pretentious	questionable	raucous	ridiculous
rowdy	rude	sarcastic	scary	scolded
seedy	shoddy	sick	simplistic	skeptical
slick	sloppy	snobbish	stressful	stupid
subjective	surly	sympathy	tasteless	terrible
tired	unacceptable	unapologetic	unattractive	unbearable
unbelievable	unbelievably	uncomfortable	understaffed	understandable
unfair	unhappy	unhelpful	unimpressed	unimpressive
uninterested	unmemorable	unorganised	unoriginal	unpleasant
unprofessional	unreal	unreasonable	unsure	unwelcome
unwelcoming	upset	uptight	useless	wary
weak	weary	weird	worse	worst

$$\begin{cases} Fnoun^{P} = \{\mathbf{f}_1, \mathbf{f}_2, \cdots, \mathbf{f}_p\} \\ Fadj^{Q} = \{\mathbf{f}_1, \mathbf{f}_2, \cdots, \mathbf{f}_q\} \end{cases} \tag{3.2}$$

Secondly, the names of countries and their citizens tend to appear in racism-related reviews. These terms were statistically analysed in this section. We could directly obtain the country names from the Address in Table 1 and then manually fill in the corresponding information of citizens. Some terms with respect to skin colour were also added, such as ‘black’, ‘white’ and ‘brown’. Finally, a special dictionary was constructed and used to determine the presence and frequency of these terms in the collected reviews. Thus, we could identify the countries that are most frequently involved in racism-related reviews.

Thirdly, we attempted to detect hate speech by using the public database Hatebase,[4] which is the world’s largest structured repository of regionalised, multilingual hate speech. Hatebase has a broad multilingual vocabulary of hate speech based on nationality, ethnicity and religion. All data are available through its web interface and API. The provided hate speech vocabularies can be used to detect abusive terms that express hatred towards a group.

3.3.5. Racism sentiment estimation

Exploring and inferring reviewers’ sentiment by analysing their online comments is challenging but illuminating. All our collected reviews are related to racism. Thus, we could understand tourists’ emotional reactions to differential treatment received due to their race or skin colour and gain insights into their implicit attitudes towards racism.

In pursuit of this goal, an approach based on aspect mechanism was used in this study. Aspects can be regarded as the content attention in a sentence. For example, in the sentence ‘I was disappointed and shocked at the treatments and racism within one’s colour’, the aspects with the top three scores are ‘colour’, ‘shocked’ and ‘disappointed’. This method can capture the importance of comment words, which are likely to represent sentences. Aspects are at the sentence level, and we could obtain the list of sentences $S^M = \{s_1, s_2, \ldots, s_m\}$ described in Section 3.2.3. All aspects in our dataset could be extracted using the method of He, Lee, Ng, & Dahlmeier (2017). After removing duplicate data and extracting stems of aspects, we divided the aspects into two groups, namely noun and adjective aspects, which are expressed as $Anoun^M = \{a_1, a_2, \ldots, a_m\}$ and $Aadj^N = \{a_1, a_2, \ldots, a_n\}$, respectively. We then represented these aspects with vectors by word embedding, with *GloVe*[5] as the adapted algorithm for word representation. Next, hierarchical clustering was used to cluster these aspects. The Dunn index was calculated to evaluate clustering quality and determine the appropriate number of clusters. Finally, cluster information was analysed to identify the focus of reviewers when making remarks and likely reveal their feelings about the experience.

4. Case study

4.1. Data collection

The data used in this study were collected from the Internet using a developed web-scraping and information extraction method, as described in Section 3.1. All identified racism-related reviews available on the website up to February 2019 were collected, resulting in a total of 4,554 reviews.

Each venue (hotel/restaurant/attraction) may contain more than one racism review. Thus, we initially counted the number of different venues. The reviews were related to 451 hotels, 991 restaurants and 641 attractions. We also analysed the distribution of reviews with regard to the three venue types. Over half of the collected reviews (50.22%) were focused on attractions, while hotel and restaurant reviews accounted for 13.68% and 36.10%, respectively (Table 2).

Amongst the review information in Table 1, the attribute values of

[4] https://hatebase.org/.

[5] https://nlp.stanford.edu/projects/glove/.

[6] The cluster of ‘Description of Emotion’ in Table 4 was highlighted with its demonstration of attitudes towards racism.

venue, address, review title and review text were consistently available in every review. However, not all reviews contained the date or user's location due to privacy considerations. A total of 182 reviews (∼0.04%) with missing date and 2521 reviews (∼55.3%) with missing user's location were obtained in our dataset.

4.2. Findings and analysis

4.2.1. Occurrences of racism in tourism reviews

This section presents some racism-related reviews on the tourism websites, which show the existence of racism in tourism reviews and the negative effects of racial discrimination on the travel experiences of tourists (see Fig. 1). For privacy considerations, we excluded the reviewers' information. In the following review examples, reviewers recounted their lived narrative and how they encountered racism in a variety of ways. For example, they were not allowed access to some places, they had to pay more to be served some services or they were obviously served poorly by the staffs. The essential reason is their skin colour. These examples confirmed the occurrences of racism in the tourism industry and indicated that racial discrimination left a negative impression on tourists about the venues and negatively affected their travel experience.

4.2.2. Temporal trend

This analysis aims to understand the trend of racism-related reviews on tourism websites up until February 2019. In this subsection, we assess the time changes on the basis of the number of reviews and venues.

Fig. 2 shows a time-series graph of racism-related reviews. The solid line describes the time change of the number of reviews containing racism, and the dashed line indicates how the number of venues changes over time. The comparison of the two results shows a generally high level of agreement from 2006 to 2019. The number of reviews is low prior to 2012, presumably because travel social networks had not yet developed into maturity and the number of registered users and online merchants was low. A slight decrease of reviews in early 2019 was also observed, which is most likely due to tourist off-season given that a consistent drop is observed in this period every year. For example, the lowest numbers of reviews and venues were from around February, from 2016 to 2018. However, it appears that ethnic prejudice did not decline despite anti-racist education from 2016 to 2018.

4.2.3. Spatial distribution

In this section, statistical analysis is used to explore the geographical distribution of racism in collected reviews. This spatial distribution is presented at the continent, country and city levels. Here, continents are roughly divided and provided by the travel website.

Fig. 3 shows the distribution across key regions of racism-related reviews and the venues focused on in these reviews. Racism exists in every continent. Specifically, Europe appears in more than 40% of racial reviews, followed by the United States at approximately 30%. Asia is ranked third with more than 10%, leaving less than 20% for the rest of the world.

Country-level data are presented in Fig. 4. These reviews are from 115 countries. Given the number of countries, we only compare the correlational results for the top 30 countries. The countries outside this list contribute no more than 1% of racism-related reviews. The United States dominates this list at 30%, and the United Kingdom accounts for nearly 10%. For better understanding, we visualise the country coverage in a geographical map shown in Fig. 5. The results of reviews on country coverage are similar to those of venues. Figs. 4 and 5 clearly show that racism is now a global phenomenon.

Fig. 6 gives the density map, in which bright colours and big spots represent venues with a high number of racism-related reviews.

4.2.4. Profiles of reviewers

An analysis of reviewer profiles aims to map the distribution of reviewers and explore the discriminatory relations by country of origin by exposing the relationship between reviewers' home addresses and tourist destinations.

Amongst the collected reviews, only 2033 reviews have User's Location information, with reviewers in this dataset originating from 1067 regions. Fig. 8 shows that tourists who posted these comments are mainly from North America and Europe. For additional details, we zoom in on the distribution in these two areas, as shown in Figs. 8 and 9, respectively. Many reviewers are located in the eastern regions of the United States, whereas reviewers in Europe are more likely to be located in the United Kingdom, Germany and France than in other countries.

This section also analyses the reviewers' tourism trajectory to explore the relationship between their origin and where they had negative racial experiences. With 719 tourist destinations (city-level) and 1067 users' locations (city-level), presenting the connections between them is complicated. Fig. 4 shows that the United States and the United Kingdom are the top two destinations where tourists wrote racism-related reviews. Hence, we selected them to illustrate the source countries of those who reported racism while travelling in these two countries. The case of the United States is shown in Fig. 10, which reveals that the majority of tourists experiencing racism here are from native American, European and Middle East regions. Fig. 11 is the origin–destination map in the United Kingdom. The figure demonstrates that people from Europe and North America are the main reviewers who mentioned racism when travelling in their online comments.

4.2.5. High-frequency terms

In this section, high-frequency nouns and adjectives are presented in a word cloud, as shown in Figs. 12 and 13.

Fig. 12 shows that the most popular nouns in racism-related reviews include 'people', 'place', 'staff', 'friend', 'food', 'experience', 'service', 'restaurant', 'club', 'manager', 'customer', 'hotel', 'bar' and 'guy'. These words are typically used when commenting on tourism services. Fig. 13 illustrates that high-frequency adjectives include 'white', 'black', 'bad', 'Asian', 'American', 'rude', 'worst', 'Indian', 'terrible' and other racism-related words apart from common words, such as 'good', 'many', 'great', 'first', 'much', 'last' and 'next'.

Figs. 14 and 15 present high-frequency terms pertaining to the names of countries and citizens by using the method in Section 3.3.4. Fig. 14 lists the terms that appear in more than 1% of all reviews. 'White' and 'black' are the most frequently used terms for skin colour, with more than 20.26% and 14.79% reviews containing these words, respectively. Terms like 'Asian', 'American', 'English', 'Indian' and 'African' occur more often, with reviews of 10.62%, 8.37%, 7.44%, 7.31%, 6.26%, respectively. Thus, these countries or their cultural backgrounds are often associated with racism in tourism research.

In terms of hate speech defined by the public Hatebase repository, some representative terms, such as 'Negro', 'Mong', 'Ghetto', 'Slave', 'Chink', 'Mick', 'Buck' and 'Idiot' could be detected in our dataset. We removed ambiguous terms found, such as 'Egg', 'Trash', and 'Crow'. The results are presented in Fig. 16.

4.2.6. Attitudes towards racism

In this subsection, we use sentiment analysis to explore tourists' subjective attitudes towards racism. As described in Section 3.3.5, all collected reviews were broken into sentences, and aspects were extracted using the method of He et al. (2017). Hierarchical clustering was used to cluster these aspects. Tables 3 and 4 show the clusters and some typical aspect examples. We place aspects difficult to categorise into the cluster of 'Mixture of Common Nouns' or 'Mixture of Common Adjectives'.

For noun aspects in Table 3, these clusters often appear in the tourism business. In addition, we are concerned about adjective aspects because people's feelings, emotions and attitudes are usually expressed in adjectives. Apart from common clusters for describing various things, we focus on the special cluster of 'Description of Emotion', as shown in

Table 4. Table 5 lists all the aspects of this cluster in alphabetical order, from which we can obtain an overall idea of tourists' feelings when they report racism by words, such as 'rude', 'aggressive', 'disgust', 'unapologetic', 'uncomfortable', 'unpleasant' and 'unacceptable'. Therefore, racism evokes tourists' dissatisfaction and negatively impacts their experience.

5. Discussion and implications

The case study affirmed the value of large-scale online tourism reviews in studying racism patterns worldwide. Few previous studies used tourism review data to investigate and explore racism at the global scale. In comparison with existing methods for data acquisition (e.g. interview and survey approaches), the proposed approach could effectively acquire a considerably larger and more comprehensive dataset of racism, which plays an important role in this work. With the support of statistics and *NLP* techniques, a series of analyses were also conducted on this review dataset to provide comprehensive insights into worldwide racism in terms of time trend, spatial distribution, semantic analysis and sentiment exploration. This study enhanced the tourism and racism research literature by further revealing the knowledge embedded in tourism reviews and attempting to evaluate the characteristics of racism experienced by tourists around the world.

Tourism data can capture comprehensive information about tourists from various countries. Benefiting from this material, we see several implications of this study for tourists themselves, tourism sectors, activist groups, policymakers and governments. Firstly, even if fluctuations were observed during some periods, we affirmed the rising incidence of racism in tourism, indicating that racism persists in the long run (Fig. 2). Secondly, the analysis of spatial distribution (Figs. 3–6) reflects the scope of racism in tourism amongst continents and countries. Racism remains a global phenomenon at present. Racism is reportedly most common in the United States, South Africa and European countries, such as the United Kingdom, France, Germany, Italy and Spain. These findings are generally consistent with the results from a survey[7] conducted between 2014 and 2015 and one previous report.[8] The comparisons with other survey results verified the effectiveness of the proposed method in this study. Therefore, racism elicits concern when tourism is developed in these areas. Thirdly, an analysis of tourists' profiles in Figs. 7–11 revealed that people from European countries, the United States, India and Australia are most likely to report racism. Furthermore, in Europe, London has the largest number of reviewers, while in the United States, the number of reviewers in the eastern part of the country is more than that in the western region. According to one report[9], the United States and Australia are on the list of countries whose citizens travel the most. In our study, tourists from these countries indeed reported a higher number of racism realities. However, the high number of Indian reviewers observed suggests that they also experience considerable racial discrimination. Finally, an analysis of racism-related terms in Section 4.2.5 presents the high-frequency terms in hate speech, which is useful in deciding the focus when detecting online racism. Section 4.2.6 demonstrates that racial prejudice negatively affects tourists' experience.

6. Conclusions

Racism is sustained by a range of attitudes, beliefs, behaviours and practices that are built on a long racial history spanning hundreds of years. Racism continues to drive inequalities and disparities in sectors such as education, employment, healthcare and housing. Traditionally, relevant racism situations are investigated by conducting population census, phone survey, questionnaire and field experiments. These approaches are time-consuming, relatively small-scale in nature and require extensive human effort. To some extent, these limitations hinder comprehensive research into racism.

With the growth of online social networking and advancements in text processing techniques, tourism research has recently shown great progress owing to large-scale review datasets. As such, we attempt to explore racism within online reviews provided by tourists to enhance the understanding on racial discrimination within this life domain. We present an approach to data acquisition that captures racism-related data and extracts information without directly engaging with tourists. In addition, the proposed method utilises statistics and NLP techniques to analyse and explore racism in terms of its tendency, distribution and semantics. Finally, the effectiveness of the proposed method is demonstrated in a case study. We achieve our aim in further elucidating reported racism in the tourism domain, with the results validating the impact of racial disparities on the travel experience of tourists.

Racism-related reviews on tourism websites reveal that, unfortunately, occurrences of racism are a serious issue when travelling. Therefore, large-scale tourism data can become a source of insight into race relations in travel and tourism. Our research has two primary contributions. One, we proposed to acquire racism information from reviews on tourism social networking at the global scale. A series of analyses of racism were conducted on the basis of this type of dataset. The dataset can also be a valuable and reliable data resource with a large sample size for related research on racism. Two, we attempt to analyse racism not only through quantitative statistics but also through content- and sentiment-based text processing techniques, making our work more comprehensive and meaningful than previous racism studies.

Although some insights were presented through the exploratory analysis, this study is not without limitations. Firstly, our research relies only on tourism reviews from one travel website. For some regions where tourism is not prosperous, limited data are likely to be collected. However, racism may still exist in these areas. Furthermore, the travel website may not be the most widely used tourism platform in some countries or regions. This limitation may bias results. Future research should consider combining multiple data sources from various tourism platforms, such as CTrip, Qunar and Tuniu, to obtain representative analysis and results. Secondly, the standpoints of people who do not travel are not included in this dataset, and involving those who do not share experiences online is not possible using this approach. Therefore, although we attempted to collect almost all publicly available racism-related data from -one travel website and demonstrated the capability of the introduced methodology, a comprehensive characterisation of racism within tourism settings and beyond still calls for future efforts from the academic and industry communities. To facilitate future research along this line, we released the collected racism-related data for public access as dataset 'Racism2019' at https://github.com/tulip-lab/open-data.

CRediT authorship contribution statement

Shu Li: Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft. **Gang Li:** Conceptualization, Methodology, Writing - review & editing, Supervision. **Rob Law:** Writing - review & editing. **Yin Paradies:** Methodology, Writing - review & editing.

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[7] https://businesstech.co.za/news/lifestyle/116644/the-most-racist-countries-in-the-world/.

[8] https://metro.co.uk/2018/06/20/racist-countries-europe-not-actually-bad-7646762/.

[9] https://www.worldatlas.com/articles/countries-whose-citizens-travel-the-most.html.

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