

High-Street Resilience and Social Media Opinion Mining

Alyson Lloyd¹, James Cheshire² and Helena Titheridge¹

¹Department of Urban Sustainability and Resilience, UCL.

²Department of Geography, UCL.

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Summary

This research focuses on the usefulness of social media opinion mining in the retail sector and what constitutes an attractive high-street retail centre from the viewpoint of a consumer. Geo-located Twitter data allows us to establish when, where and what people say about different retail centres. Comparing this data with retail centres of differing vitality could allow us to draw conclusions about how useful and predictive this source could be. Initial analysis revealed some contrasting text content within top ranked and bottom ranked retail centres in Greater London.

KEYWORDS:

Opinion Mining; Consumer Behaviour; Social Media; Retail; Resilience

1. Introduction

British town centres and high-streets have experienced substantial change over the last decade (Wrigley and Lambiri, 2014). However, not all high-street retail centres have responded in the same way – some appear to be more resilient than others. There is therefore an increasing need to reassess what constitutes “resilience” in the context of the UK’s high-street retail centres (Coca-Stefaniak, 2013).

1.1 High Street Resilience

Research has so far focused on town centre size or ‘diversity’ (the existence of small independent vs. corporate retailers). However, there has been little substantive research in this domain, with existing work offering conflicting perspectives. If we want to assess/compare high-street retail centre performance, we need to establish clear definitions of their structures (Wrigley and Lambiri, 2014). Retail specialists Harper Dennis Hobbs (HDH, 2014) have recently created the first metric based on multiple variables for British retail centres - *the Vitality Index*. This ranks the top 500 retail centres across the UK, taking into account previously ignored factors such as the proportion of luxury retail, ‘out of fashion’ retail tenants (e.g. charity shops), vacancy rates and spend. However, although the *Vitality Index* offers insight into high-street vibrancy based on its units, it tells us little about what attracts consumers. With the rise of online and convenience retail, it is necessary to also understand this. There is significant evidence to suggest consumer experiences also contribute to high-street vibrancy.

1.1.2 The importance of customer experience

Hart et al., (2014) recently revealed that factors such as atmosphere, social interaction and markets are all aspects that attract consumers to specific retail areas. Good varieties of fashion/clothing units were also particularly attractive (accounting for the most purchases across different locations) and social interactions appeared to play a vital role. Places that facilitated these interactions (cafes, restaurants) heightened enjoyment, prolonged dwell time, increased spend and deterred consumers from the online alternative. Such findings highlight a few of the complexities that are encountered when we consider high-street performance from the perspective of the consumer. For example, it suggests that the more cafes or fashion units available, the more vibrant the high-street may be. Wrigley and Brookes (2014)

similarly emphasise how we must understand the way town centre users ‘interact’ with the retail centre environment in order to understand its resilience.

1.2 Measuring Perceptions - Opinion Mining

Whilst the rise of digitalisation may have caused issues for high-street retail, it could also offer some answers for the future. For example, the growth of online social media platforms, blogs and online review sites has led to large availability of opinion rich textual sources. Opinion mining refers to the processing of natural language for tracking the mood and opinions about a particular topic or product (Pak and Paroubek, 2010). With 70%-80% of business information (such as social media, texts, emails and feedback forms) now coming in this unstructured, textual format (Xu and Li, 2013) the area of opinion mining has become of particular interest to the business world.

1.2.1 Opinion Mining with Twitter

Twitter (an online social networking service that enables users to send and read short 140-character messages called "Tweets") has so far produced some useful applications in the field of opinion mining and urban dynamics. For example, predicting movie sales revenue (Asur and Huberman, 2010), understanding what voters are thinking during political campaigns (Pak and Paroubek, 2010) and predicting stock market activity (Bollen et al., 2011). Twitter also allows for ‘geo-tagging’ (adding spatial location about where a message was sent) and accurate time stamps. Such sources mean that consumers now have the power to share their brand experiences and businesses are able to utilise these for insight. Taking into account these applications in other domains and the ability to mine geo-located opinions, is it possible that we could utilize this information for retail centre insight?

1.2.2 Limitations of Social Media

Whilst the applications are promising, there are limitations of mining social media text. For example, such data is only generalizable to people that engage with it. However, as predictive and useful results have been demonstrated in other domains, it is still necessary to understand the possible contributions and/or limitations to the retail sector. Also, opinion spamming (Jindal and Liu, 2008) refers the fact that social media enables anyone to express views with anonymity, therefore, data could be susceptible to fake opinions. Twitter messages are also short and can be too noisy (often containing abbreviations, acronyms and slang) to enable reliable automated opinion classification. Nevertheless, recent methods are beginning to address these issues (Hu et al., 2013) and findings from other domains deem it worthy of investigation.

2 Current Research

2.1 Method

This research offers a preliminary assessment of the usefulness of social media opinion mining for capturing public opinions of retail centres. Twitter content that has been geo-tagged within specified high-street retail centres will be analysed for content, topics and sentiment. Tweets will be selected that are within 500 metres of a retail centre location of interest. This distance was considered a suitable starting point to incorporate text of interest, yet exclude tweets outside of the retail location. However, catchment areas for retail tweets may be modified (for example to include network based distance thresholds) as research progresses. With intent to focus specifically on what constitutes a resilient *high-street* retail centre, large shopping centres such as Westfield London will not be considered.

Analysis of Tweet catchment areas will begin by assessing general content and word frequencies. Topic analysis will then be conducted to establish a general feel of activities and conversation topics in that area. Sentiment analysis will also be performed to establish public mood about a retail centre. Using the HDH *Vitality Index*, Tweet analyses can then be compared with retail areas of differing vitality in London (see Table 1).

Table 1: Example of rankings from the HDH Vitality Index: Top 5 and bottom 5 retail centres in Greater London (2014).

Greater London

Top 5 Vitality

HDH Vitality Ranking	Retail Centre	HDH Vitality Score (0-400)	HDH Retail Spend Potential	HDH Retail Spend Potential Rank
1	Westfield London	312	£2,265,528,498	13
2	Chelsea	290	£795,283,829	98
3	Knightsbridge	261	£675,270,025	128
4	Canary Wharf	254	£563,390,481	149
5	Brent Cross	246	£1,501,294,061	36

Bottom 5 Vitality

HDH Vitality Ranking	Retail Centre	HDH Vitality Score (0-400)	HDH Retail Spend Potential	HDH Retail Spend Potential Rank
295	Barking	42	£173,655,727	348
311	Hammersmith - King Street	40	£259,043,032	282
356	Edmonton	31	£214,424,214	324
359	Orpington	30	£236,356,303	307
380	Wembley	27	£91,816,607	395

The Local Data Company (LDC), who specialise in maintaining accurate and current locations of retail centres around the UK, provided the retail centre location data. There are 291 retail centres in Greater London (see Figure 1).

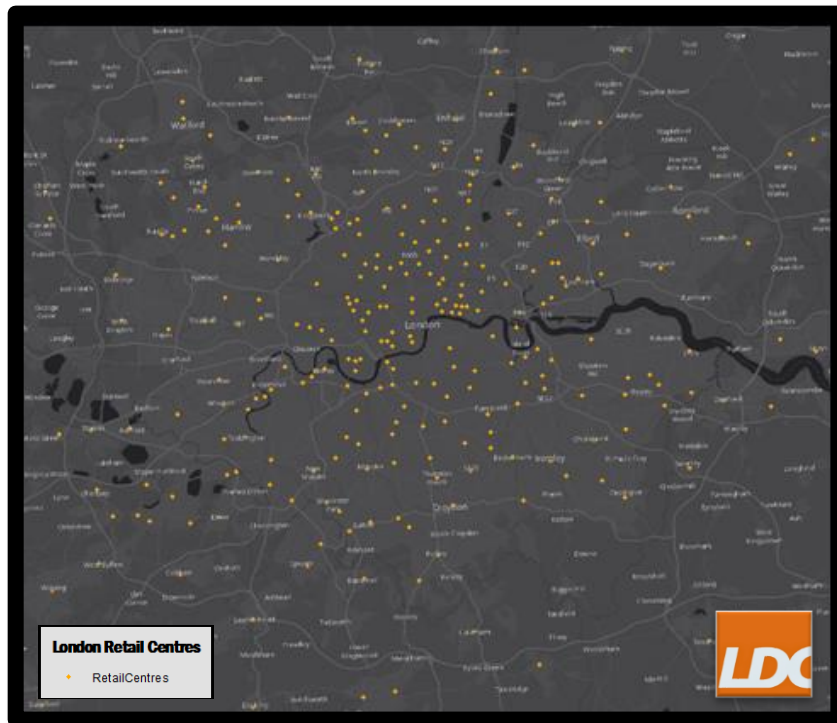


Figure 1: Retail Centre Locations in Greater London.

2.2 Analysis

Buffers around retail centres were created and tweets within these selected using R. Figure 2 shows the result of this for two of the top and bottom ranked high street retail centres in Greater London, according to the HDH vitality ranks (Knightsbridge and Chelsea, Orpington and Wembley).

KNIGHTSBRIDGE



CHELSEA



ORPINGTON



WEMBLEY



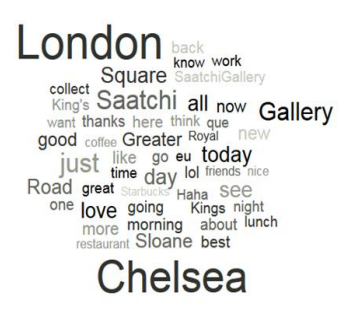
Figure 2: Maps displaying tweets sent within the top and bottom ranked retail centres in Greater London.

The Knightsbridge catchment area contained 2836 tweets from 2117 users, Chelsea contained 1200 tweets from 947 users, Orpington 347 tweets from 204 users, and Wembley 260 tweets from 158 users. Tweets from these locations can be transformed into wordclouds for early assessment of content and word frequencies (see Figure 3).

KNIGHTSBRIDGE



CHELSEA



ORPINGTON



WEMBLEY

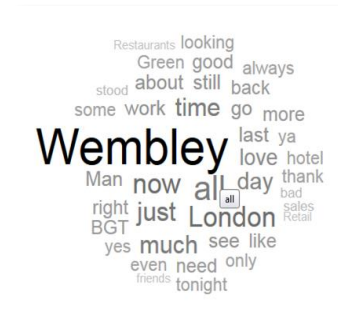


Figure 3: Word Clouds displaying the 50 most frequent terms within the two top and bottom ranked retail centres in Greater London (*where larger term means a more frequent occurrence*).

From this initial examination, we can see that content does differ within the top and bottom ranked locations. As expected from natural language, there are many common words within the four areas (“all”, “more”, “like”), however, in the top ranked centres, there are considerably more topics indicating social interactions (“lunch”, “café”, “gallery”, “friends). On first appraisal frequent terms in the bottom ranked centres appear to be much more negative (“sales”, “bad”, “money”, “hungry”) than the top ranked terms, however future sentiment analyses will be able to expand on this.

3 Concluding Remarks and Future Work

Research has begun to examine the usefulness of social media opinion mining in the retail sector. Initial analyses shows that people may tweet about more socially interactive activities in the top ranked areas. However, whether there is a relationship between this and the vibrancy of the retail centre remains to be concluded. It is recognised that both top ranked retail areas are located much more centrally to London than the bottom ranked, therefore such activities are much more likely to occur. Also, there are considerably more tweets and users within the top areas. Nevertheless, further analyses will incorporate many retail centres and tweet/user rates across Greater London for fairer comparisons.

Future research will look to investigate the extent of retail tweet catchment areas and obtain further data from the Local Data Company such as high-street vacancy and occupancy. This could be combined with a measure of consumer perceptions to establish a novel metric of what constitutes a vibrant and attractive retail centre.

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5 Biography

I am an M.Res student within the Department of Urban Sustainability and Resilience at UCL, undertaking my first year of a PhD studentship in Retail Sustainability and Resilience. My interests are in consumer behaviour and spatial analysis in the retail sector. I completed my undergraduate degree in BSc Psychology from Cardiff University earlier this year.

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