

# Estimating real-time highstreet footfall from Wi-Fi probe requests

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## ABSTRACT

The accurate measurement human activity with high spatial and temporal granularity is crucial for us to understand the structure and function of built environment. With increasing mobile ownerships, the Wi-Fi probe requests generated by these devices can be an excellent source of data for such measurement. The major challenges in using Wi-Fi technology for such purpose are precisely delineating the field of measurement and arriving at accurate estimates without compromising the privacy of the users of the mobile devices. In this paper we demonstrate that, with the application of class intervals and a novel graph based technique, we can overcome the challenges and reliably measure real-time footfall at retail highstreets in London.

## KEYWORDS

Highstreet footfall; Wi-Fi Probe requests; Sensors; MAC Randomisation

## 1. Introduction

In the past decade Wi-Fi has emerged as the most commonly used technology in providing high speed internet access to mobile devices such as smartphones, tablets and laptops in public and private spaces. This has resulted in multiple Wi-Fi networks being available at almost every location in dense urban environments. Traversing through this overlapping mesh of Wi-Fi networks, modern mobile devices with Wi-Fi antennae regularly broadcast a special type of signal known as 'Probe Requests', in order to discover Wi-Fi networks available to them. This helps these devices to connect and switch between the WiFi networks seamlessly.

Probe requests are low level signals standardised by IEEE 802.11b/g specification (IEEE 2013) as the first step in establishing a Wi-Fi based connection between two devices and is implemented in any Wi-Fi capable device irrespective of the manufacturer or the model. This ubiquity and standardisation make them an excellent source of open, passive, continuous, and wireless data generated by Wi-Fi capable devices present at any given time and location. Considering the unprecedented levels of mobile device ownership in recent years, we can in turn use this data to understand the population distribution in highly dynamic urban environments with high spatial and temporal granularity (Freudiger 2015, Kontokosta and Johnson 2017).

While a Wi-Fi based method to collect data offers us various advantages such as, easy scalability and efficiency in terms of cost and time, It also introduces few system-

atic biases, uncertainties in the collected data along with the serious risk of infringing on the privacy of the mobile users. In this paper, using a set of probe requests and manual counts collected at various high street locations across London, we demonstrate that pedestrian footfall at these locations can be estimated with considerable precision and accuracy while protecting the privacy of the pedestrians.

## 2. Previous Work

There have been numerous attempts at using Wi-Fi to measure the volume and movement of people in the built environment for various applications (Zarimpas *et al.* 2006, Sapiezynski *et al.* 2015, Rekimoto *et al.* 2007). Though most research obtains feasible and favorable results, in recent years, one of the major challenges faced in such attempts has been the MAC address randomisation process. This process aims to protect the users' privacy by anonymising the only globally identifiable portion of the probe requests, which results in a set of probe requests generated by the same device with different random MAC addresses (Greenstein *et al.* 2008). There have been various successful attempts by researchers to breaking this randomisation process in order to extract real MAC addresses, (Martin *et al.* 2017) but this usually results in serious risk of infringement of the privacy of the users of the mobile devices. There is a clear gap in the research for exploring methodologies which enable us to estimate the number of unique mobile devices from a set of anonymised probe requests, without the need to reveal their original MAC addresses.

## 3. Methodology

The primary aim of this research is to enable us to collect a series of probe requests and process them into an usable pedestrian footfall count. We do this by using a Wi-Fi receiver to collect probe requests broadcasted by mobile devices, filtering out the background noise and aggregating them based on the device that generated them. We begin by looking at the characteristics of probe requests in detail, devise a methodology to collect these probe requests in public areas, examine the systemic biases and uncertainties in the data collection method and device data processing methods to overcome these challenges. Finally we compare the processed footfall counts to the ground truth recorded by primary surveys.

### 3.1. Probe Requests

Probe requests are a special type of management packets broadcast by Wi-Fi enabled devices as part of the various functions such as scanning for available access points (AP), quick geo-location by triangulation based known APs, etc. These are broadcast by all Wi-Fi enabled devices regardless of the manufacturer, type or model of the devices though there is some variation on the frequency and the information transmitted through them. In some cases, such as Android devices, these are broadcast even when the Wi-Fi functionality has been turned off by the user. Thus these signals can be used to reliably identify the presence of Wi-Fi enabled mobile devices.

Being a first step of connection initiated by the mobile device, these packets have information regarding the characteristics of the mobile device itself. Some of the key information we can infer from these requests are,

- (1) Media Access Control (MAC) address which is an unique identifier for the wireless hardware of the mobile device,
- (2) Sequence number of the request for the mobile device to keep track of the responses,
- (3) Timestamp at which the request was received by the AP,
- (4) Total length of the request in number of bits, and
- (5) The strength of the signal which transmitted the request.

The MAC address is the primary unique identifier for the mobile device. It has two parts, first part gives information about the manufacturer of the device and the second is unique to the device. The MAC address can be randomised (hence non unique) and is marked as such. Though sequence number and length of the packet are not strictly unique, we hypothesize that we can use them to estimate unique devices.

### **3.2. Data Collection**

The data collection involved two processes - A sensor based collection of probe requests and a manual count of pedestrians in the area next to the sensor. We have detailed the sensor design below,

The sensor consists of wireless transponder in a linux/ MacOSX based machine which is put into a monitor mode and wireshark software (tshark) is used to sniff, filter and save the relevant packets. The filters applied are management frame to probe requests to broadcast. This is then parsed, personal information is hashed, compressed and sent to a server via web socket protocol. The server receives, logs and stores the data in a postgresql database, for further analysis. The manual count was undertaken using an Android application on a mobile phone where timestamp of every individual pedestrian footfall was recorded by touch screen. A schematic is shown in ref figure.

### **3.3. Estimating Footfall**

The next step after collecting the probe request is to estimate the footfall or pedestrian activity from them. There are three major challenges in the above data collection methodology. the first one is deliniating the area of interest. WiFi and its range depends on lots of factors. need a way to isolate the noise from the relevant data. depends a lot on microsite so we need a methodology which provides us with a general solution without much tinkering. Second one is the mac randomisation. modern phones randomise their MAC addresses to avoid detection and tracking. This leads to overcounting and explosion of randomised (local) mac addresses. We need a non MAC dependent method to overcome this. Finally, inherent mobile phone carrying bias. we need to account for the average mobile ownership. which is steadily increasing and is not 1:1.

#### *3.3.1. WiFi range*

One of the clues of the distance of the device generating the probe request is the strength of the signal recieved from it. The Signal strength varies in inverse square law over distance with a propagation constant. It also depends on lot of micro site, micro temporal factors. There cannot be a simple rule to fit and filter for all configuration. Our hypothesis is that in a specific setting and specific source of noise, there must exist a clear break in the data. for example, if there is a phone shop next to our sensor

where hundreds of phones regularly send lots of probe requests we should be able to see a large increase in number of probe requests around a specific signal strength. we can identify this sharp change/ break using class interval algorithms such as k-means, jenkins, quantile, etc.

### 3.3.2. *MAC randomisation*

This is a recent problem. ref in figure. how mac randomisation has caused problem MAC address has been our unique identifier. Now we need to look for others. the contenders are length, duration which seem to be unique for device sets of known wlangs and capabilities which can give us unique finger print and finally sequence numbers in the packets. This is a tricky one since it is neither unique nor aggregatable. we need a method to separate sequences shown in fig. We propose a graph based clustering algorithm where each cluster corresponded to a unique device. The algorithm creates a graph where the probe requests represented the nodes, and links are created between them based on the following rules:

- (1) A link could go only forward in time.
- (2) A link could exist between nodes with a maximum time difference of  $\alpha$  (time threshold).
- (3) A link could go from low to high sequence numbers.
- (4) A link could exist between nodes with a maximum sequence number difference of  $\beta$  (sequence threshold).
- (5) A node could have only one incoming link and one outgoing link, which is the shortest of all such possible links.

The nodes were then classified based on the unique connected component they belonged to. This classification was assigned as the unique identifier for the anonymised probe requests this unique identifier is used instead of MAC to aggregation.

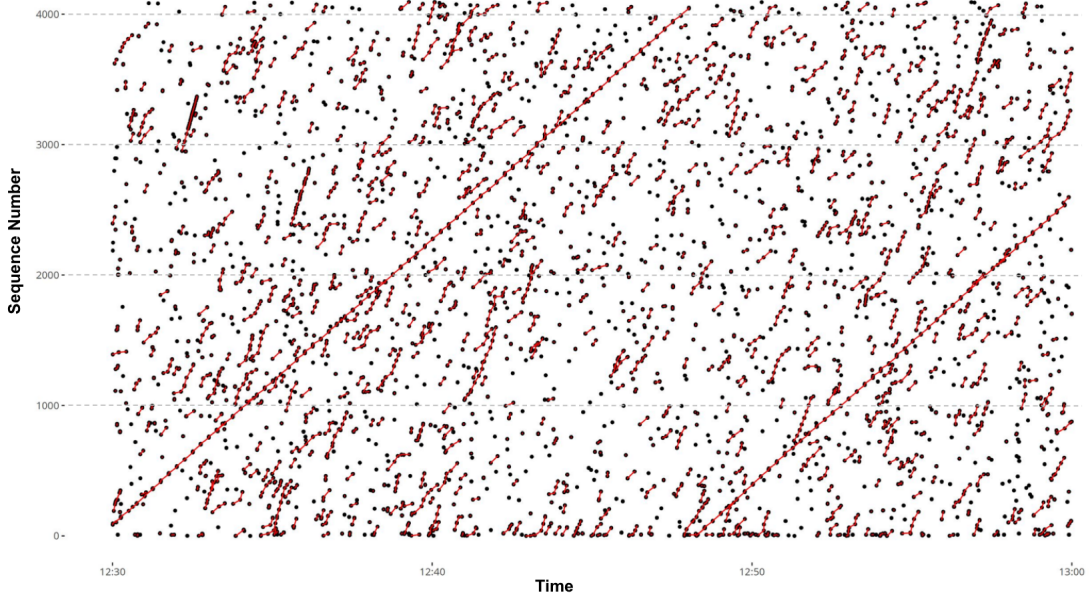
### 3.3.3. *Mobile phone ownership*

This is both a long term change and result of demographic factors. Phone ownership is not 1:1. It changes slowly overtime. It also changes with place to place. It can be more in dense urban centers and can be low in rural areas. We propose a adjustment factor methodology we use periodically carried out manual counts to adjust the numbers to what is reported on ground. The adjustment is as strong as the amount of ground truth we collected.

## 4. **Pilot Study**

We conducted a pilot study to get a feel for the data. See which fields are relevant and which ones are not. to check if the sequencing algorithm holds true. to find out which one of the classification algorithm works. if these methodology works in real world scenario scalably. A pilot survey was conducted on Oxford Street in London in December 2017, where two sets of data were collected on pedestrian footfall with the aim of establishing merit in measuring pedestrian footfall as a function of the number of wifi probe requests collected at a given location. These datasets were collected through Wi-Fi sensing and manual counting in parallel.

Being located at one of the busiest retail locations in the United Kingdom, the WiFi



**Figure 1.** Clustering probe requests based on increasing sequence numbers present in them.

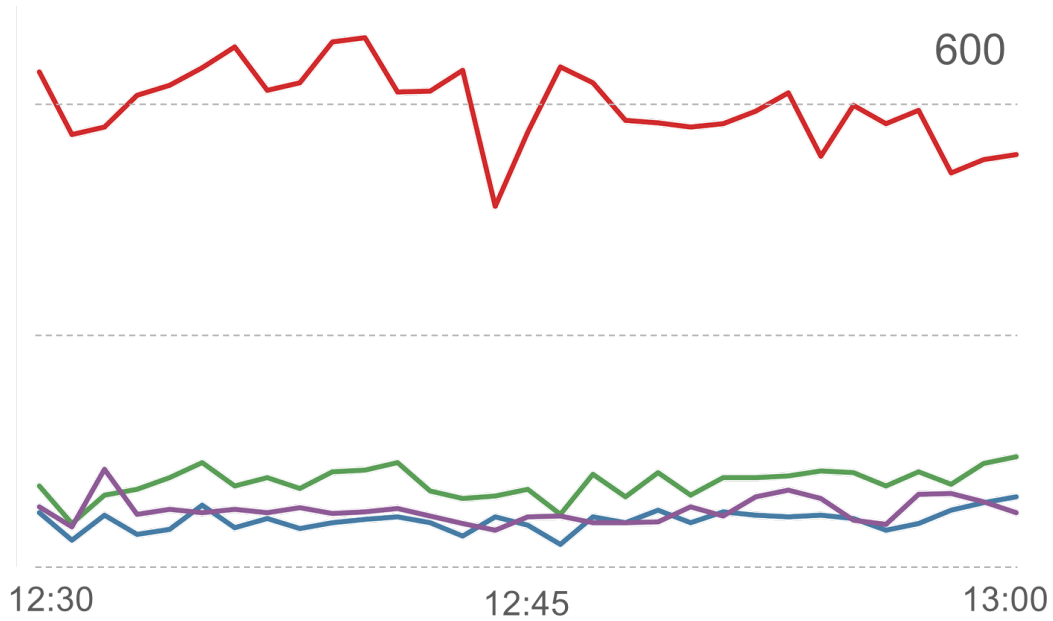
sensor captured approximately 60,000 probe requests over a 30 minutes interval, and 3,722 people were counted manually.

When we aggregated the probe requests by their MAC address for every minute, the difference between the sensor counts and the manual counts was observed to be on average 425%. This suggested that there was a large amount of noise in the data which might have included signals from devices outside the area where the manual count was conducted, as well as anonymised probe requests from the same devices but with different MAC addresses. This process of filtering was highly effective and reduced the difference between the sensor counts and manual counts to 30%. We observed that around 55% of all probe requests collected were anonymised. We assigned the hashed MAC address the unique identifier for the remaining 45% and investigated the anonymised probe requests further.

An initial analysis revealed that the fields - SSID and tags - were very sparse and did not provide much information for our cleaning process. In addition, the duration field was closely related to the length of the probe request and provides no new information. Therefore, we removed these fields from further analysis. We eliminated the noise from devices outside the area of interest by removing all the probe requests which reported a "low" signal strength. This classification of "high" vs "low" was performed using a k-means classification algorithm. The cut-off point for the collected data was -71 dBm.

Figure 1 shows the clustering process: the black dots show the probe requests and the red lines connect them into clusters representing those which were generated by the same device. We finally combined both normal and anonymised probe requests, aggregated them based on their unique identifier, and removed repeating probe requests which reduced the difference between the sensor counts and the manual counts to -18%.

we find that the methodology works as shown by the reduction in the mean error. We find kmeans and quantile best algorithms for filtering sequencing works. Even in densely populated areas.



**Figure 2.** Comparison of counts after filtering with manual counts

Though this is promising we need to know more to generalise the methodology. we do a detailed multi location, longer term study with multiple manual verification which is the main study.

## 5. Main Study

The aims of the main study are, test the validity of the signal strength algorithm in different micro site conditions. Test that the sequence number algorithm works in real world for different locations and different times. check if the thresholds are consistent. Test if the calibration works over intervals Finally conclude if we can estimate footfall confidently with just probe requests.

five locations were selected across central london which had different types of configurations and specific problems configurations are shown in fig. map is shown in figure.

- (1) Phone Shop Camden - has phones and bus stops.
- (2) Restaurant TCR - has seating area on either side.
- (3) Holborn Information Kiosk - High volume station entry
- (4) Restaurant Russell Square - seating on one side and side walk on other
- (5) Shop Charring Cross - sidewalk on one side and phone shop next door

Installations were carried out over the time period from xxxx to xxxx. the data collection happened from xxxx to xxxx. Manual counting was carried out with high precision on dates xxxx and aggregated five minutes on xxxx. The difference in methods could lead to some inaccuracies in data. The overall schedule is shown in half page graphic.

The overall statistics of data collected. How many probe requests. Comparison of location in terms of volume, patterns in daily footfall etc. The comparison between global and local. comparison between different types of vendors. Specifics on top 5 manufacturers.

We do a daily analysis of distribution of signal strengths. The thresholds are shown in the table. The average is xxxx and standard deviation is xxx. we notice that the variation is lot. There is a definite change with the micro site locations.

We see how the signal strength filtering affects the counts. compared to manual counts we look at the average mean errors (daily) per 5 minutes. The counts go as follows. Shown as a red line in the Figure.

We can conclude that even though it has variations, this is a good method to reduce the overall level of error.

This is also done for different locations hourly for all the data we had. we compare it to the manual counts and see that the average mean error has been reduced/increased. The finger print works well for all the locations. It also works over a period of time and gives us a comparable and close footfall count to the manual count. The thresholds found in the pilot study works as well.

Finally we normalise the sensor counts to match the manual count using a fraction/adjustment factor calculated from the know manual counts. we have three sets of counts. We check if the adjustment factor holds the same in all three counts across locations. It does with a variations from xxx to xxx. The results are shown in the table.

we see that the signal strength filtering works and reduces error by xxxxx. there is variation by locations. we see that sequence number algorithm works as well. The threshold stays constant well and works well across locations. The calibration also works and ajustment factor stays consistent short term. This needs more work long term.

## 6. Conclusion

We have established methodology for collection and estimation of footfall from Wifi data. It is important to note that the filtering process was done based solely on the information present in the probe requests and their temporal distribution. This ensured that although the mobile devices were uniquely identified, there was no further personal data generated by linking the probe requests to the users of the mobile devices. This method essentially gave us a way to estimate the footfall in real-time without identifying or tracking the mobile devices themselves. A real time footfall in these locations are shown in the figure. A dashboard can be found at xxxxx.

This Wi-Fi based footfall counting methodology offers a large number of applications and benefits for real time spatial analysis. Since Wi-Fi based sensors are inexpensive and the data model is scalable, it is possible to use this methodology for a large network of sensors to gather granular data on pedestrian footfall. Projects such as SmartStreetSensors (CDRC 2016), may utilise this methodology to overcome the challenges introduced by the implementation of MAC address randomisation. Such precise and granular data also enables us to confidently model the pedestrian flow in urban road networks, and will be an indispensable tool in the smart city framework. It can also be used to understand and classify geographical areas based on the spatio-temporal distribution of the volume of activity in them.

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