Beanstalk - A Community Based Passive Wi-Fi Tracking System for Analysing Tourism Dynamics

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ABSTRACT

This paper presents Beanstalk, an interactive platform to assist communities in easily running systematic analysis of mobility patterns of tourists at their destinations, contributing in new ways in visualizing spatio-temporal mobility data for forecasting, tracking trends, detecting patterns and noticing anomalies. The approach takes advantage of a combination of passive Wi-Fi tracking and ground truth data provided by tourism authorities. By analyzing a large dataset for a medium sized European island, we provide evidence of the accuracy and effectiveness of this low-cost method in inferring topological characteristics of tourist behavior and relevant typologies of trip itineraries. This helps decision makers in the touristic sector to plan and manage actions geared towards improving the sustainability and competitiveness of their touristic regions. In particular, we argue that in a world where sensing data is becoming inexpensive, there is an opportunity to use this approach to deliver data back to local communities which are empowered to act and leverage this information.

Author Keywords

Spatio-temporal data; Community-analytics; Human-Data Interaction; Activity Tracking.

ACM Classification Keywords

H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous;

INTRODUCTION

We are living in a data-centric world. The environment is increasingly becoming more instrumented and interconnected as pervasive sensors and devices are generating vast amounts of data, which in turns produces new insights and knowledge about the world we live in, useful to society at large. In this context, one particular area of interest is Tourism, a continuously growing and important sector for many regions and countries worldwide for which it is a central and important source of welfare. In particular, in this area of interest, spatio-temporal data play a key role to understand tourism evolution and social commodity [11].

Following this line, we here present a case study focusing on the development and deployment of Beanstalk, a low-cost passive Wi-Fi tracking infrastructure for gathering data in a non-intrusive way, with the aim of exploring the possibility of providing a wider community of stakeholders with information about spatio-temporal patterns about the movement of people in touristic destinations. In order to do that, we provided 60 locations on Madeira Islands, a well-known European touristic destination in which tourism widely contributes to the local economy, with our passive Wi-Fi tracking system. Over a period of 60 weeks, we collected mobility data on 11 million unique devices, resulting in a total of 274 million data points. In addition to collecting the mobility data, we also provide a ground truth for our data, made available by the local authorities and the tourism board, about events and flows of people in the main gateways, such as airports and ports.

This work also contributes in new ways in visualizing spatio-temporal mobility data for forecasting, tracking trends, detecting patterns and noticing anomalies. Most existing analytics tools are aimed at experts that learn complex interfaces and understand the language of analytics. This limits the extent and types of people that can access this data. Instead, our system can be easily used by small businesses and organizations who, by consulting the data visualizations provided by it, can make sense of some local phenomena and take actions that contribute to improve their tourism related offerings and the wellbeing of the local context.

This will help a large set of decision makers in the tourism sector to better plan and manage actions geared towards improving the sustainability and attractiveness of their touristic activities. In fact, unlike other methods, our approach does not rely on expensive field surveys nor access to proprietary network or analytics sources which result in a limited practical usefulness of the approaches employed and the results obtained for policies and the management of touristic regions (as, for example [10]).

The paper starts with an overview of related work and then the system is illustrated, detailing the passive Wi-Fi tracking

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infrastructure and the interactive web platform. Then, we present the obtained findings, and finally, we conclude the paper with discussions and future works.

RELATED WORK

This research is primarily motivated by two areas of prior work, as detailed in the following Subsections.

Studies on Urban Mobility

Many studies were conducted looking at how mobility tracking and analysis on urban environments could be used in order to estimate: daily commutes, usual travel distances and route planning. Jiang et al. [6] presented several statistical and data mining techniques to understand the urban spatial structure from travel surveys. In their work they detect clusters of individuals by daily activity patterns and usage of space/time among groups of citizens. Dixon [4] used the data from mobile phone call records from Ivory Coast to assess the mobility patterns of the citizens, by trying to map the routes between the GSM communication antennas providing this information through a web based prototype tool to visualize the data. Several studies have at- tempted to locate or count the number of people in specific locations. Most of them use wireless technologies, with a large part of them exploring technologies such as RFIDs [8] or Bluetooth [1]. The GSM technology was also explored by Sohn in [15] analyzing radio signals with signal strengths, cell IDs, mobile network code, mobile country code, location area code, and channel numbers from fixed sources, and then estimating the movement of the users.

Several studies used Wi-Fi technology to capture human mobility information in highly crowded areas such as football games, universities campuses and hospitals [2] [1] [13]. The motivations of many of these studies are diverse, some look at energy waste on scanning methods [1], realistic facility management and planning [13], while others looked at crowding factors, flock detection and waiting times, speed and frequent paths [15] [7] and even social information like popularity of events (in the case of [2] singers in concerts). Several networking infrastructure vendors offer geo-marketing solutions for organizations deploying large Wi-Fi networks (such as shop- ping malls, hotels and airports). However, concerns about the privacy issues related to these systems make information about them hard to find. Several attempts to deploy similar systems in public parks (e.g. London Hyde park[1] and Olympic Park[2] and New York Bryant Park[3]) and airports (e.g. Helsinki[4]) have reached the media with concerns about privacy and commercial use of tracking information.

To the best of our knowledge none of the academic studies lasted more than days or weeks and they focused on a particular area (typically a campus, park or infrastructure).

Network Analysis and Profiling

There are several techniques to analyze and synthetize mobility information from tracking data. For instance, in [9] the authors inferred mobility data from Wi-Fi logs on a University campus using the RADIUS protocol. The movement data was analyzed in terms of stays, leaps and moves. In [14] the authors present a study of human mobility using six months of high temporal resolution Wi-Fi and GSM traces. The authors demonstrate how it is possible to estimate the location and use of Wi-Fi access points using only one GPS observation per day, per person. The results reveal an opportunity for using for using ubiquitous Wi-Fi routers for high resolution outdoor positioning, but also alert for the significant privacy implications of such techniques [14]. An advanced method used in a study from [3] used the information broadcasted from 8000 Wi-Fi devices in Australia to perform what the authors called SSID profiling. This technique, involves analyzing the captured information, focusing on the SSIDs (names of the networks saved on the devices) to associate different devices with social connections. It uses algorithms used on texts similarity, where each SSID is considered as a word. Those connections attempted to locate people that visit the same places, share the same interests, or family bonds.

METHODS, DEPLOYMENT AND DATASET

Wi-Fi technology is the main solution for medium range communications, and is increasingly embedded in smart objects, smart-phones that use this interface for cheap and fast access to the Internet. Modern Wi-Fi protocols feature robust encryption/authentication mechanisms; however, the headers of many Wi-Fi frames is transmitted freely. This means, that the MAC address of the devices (a unique identifier) can be collected and used to distinguish the device. In addition, emission of Wi-Fi frames is not limited to the time when the device is connected to a Wi-Fi network. Due to active service discovery mechanisms enabled on most devices, Wi-Fi interfaces are periodically broadcasting frames, named probe requests, that contain their MAC address. As a result, a device with a Wi-Fi interface turned-on, acts as an actual wireless beacon by periodically advertising in clear a unique identifier [3]. This advertisement is also done while using the location services (GPS) in high accuracy mode that use the Wi-Fi network discovery to narrow down the device location in places where the location service takes longer to connect.

The mechanism to determine when to search for networks is not defined by the IEEE 802.11 Wi-Fi standard, which is left for vendors to implement. The same applies for strategies to protect the privacy of users that some vendors started implementing recently. These are based on randomization of MAC addresses implemented for instance in iOS 8 (since

[1] http://www.independent.co.uk/life-style/gadgets-and-tech/news/updated-londons-bins-are-tracking-your-smartphone-8754924.html

[2] http://www.independent.co.uk/life-style/gadgets-and-tech/news/updated-londons-bins-are-tracking-your-smartphone-8754924.html

[3] https://www.engadget.com/2016/08/24/new-yorks-bryant-park-is-tracking-visitor-behavior/

[4] http://www.dailymail.co.uk/travel/travel_news/article-2710491/Helsinki-Airport-track-passengers-using-mobile-phone-WiFi.html

2014), Android 6 (since 2016), windows 10 and Linux (since kernel 3.18) [16]. Regardless, several reports [3] [16] and our own tests show that it is still possible inferring interesting information using a passive Wi-Fi tracking approach, also considering that randomization of MAC addresses is still incipient.

SYSTEM WALK-THROUGH

There are many solutions to implement Wi-Fi monitoring, ranging from commercial solutions costing thousands of euros, to custom-made solutions based on Raspbery Pi. After considering the options, we decided to use a commercial TP-Link MR3240v2 home router (costing around 45€) to capture the data. This solution was capable of running a Linux system, and since we were targeting multiple locations and wanted a robust solution, we opted for installing OpenWRT – Barrier Breaker 14.07. It had the necessary wireless interfaces, the antennas encapsulated in a protection case, and featured a USB port just like the other embed systems. Both the internal memory and the swap memory were expanded with an external flash drive with a minimum of 512MB (256MB for storage and 256MB for swap). This flash drive was used in the USB port that was originally designed for the 3/4G modem announced as a feature of this router.

The wireless interface was assigned to a single network, and configured to monitoring mode. This ensures that no network name is broadcasted, denying the possibility to gain access to the device wirelessly. It also hides the router from other capturing devices, since it does not broadcast packets, and simply monitors the surrounding traffic. For this study, we chose to listen to the channel 11 since it is one of the three recommended non-overlapping channels (1, 6, 11) [5], so as to reduce the interference from other of channels and frequencies, and to increase the changes that more devices could be operating in this channel. Moreover, the chosen channel doesn't influence the capture, because the devices cycle through all the channels in the active scan.

A custom script in Python was added to run at the start scripts of the router, setting the wireless interface in monitoring mode. This basic script uses the package Scapy to capture packets and filter them for the type 0 (management) and the subtype 4 (probe requests). It also takes into account the big number of repeated messages (same MAC address and SSID) from the same device, and doesn't send to the database repeated captures to avoid data duplication. It is also programmed to record the data internally in the flash drive storage, when the connection to the receiving service is not available - caused by server down time, or internet unavailability - and sends the internal backups when the connection is restored. The probe requests detected are sent to a remote database through a web service with JWT authenticated messages in HTTP requests.

It is important to notice that the MAC addresses detected in the probe requests were locally transformed using a cryptographic hash function to prevent access to the original identifiers that could be used to compromise the privacy of users. The result is stored in a MySQL database.

The server side components perform the calculations and optimizations required for analyzing the captured data and provide the results through a web server to the clients. The Wi-Fi routers are connected to a VPN allocated on the server to allow their remote management, and the scripts processing the data interact with several external services and APIs. Figure 1 shows the system architecture components.

Data processing

The data is processed with MySQL procedures and custom scripts into summary tables originating from the probe requests, MAC addresses and SSIDs to provide a quick way to access and visualize the processed data. Daily and hourly counts are performed by counting the number of unique devices for each location. Meta information about the MAC addresses is also processed regarding the number of days they appear on the system, first and last appearance, and the brand of the WiFi card (derived from the first 3 bytes).

The daily procedures also calculate the leaps take by the same device between different POIs (Point of Interests), helping to build route trends and paths calculation. Other analysis is also done regarding statistics of the SSIDs and MAC address meta information, such as the first and last time it appeared on the system, the number of days active, and the age (difference in days between first and last appearance).

Event detection

After the system was installed we started noticing spikes in the data denoting recurrent or unique events. For instance, at the airport and port the system captures the flows of people corresponding to the arrival or departure of planes and ships. Similarly, we noticed unusual events corresponding either to patterns of flow (weekdays vs. weekends) or sudden events (a concert, an exposition or even a football match). Therefore, we implemented an event detection algorithm trying to automatically identify abnormal occurrences in the data. Similar to [7] we consider an event (or flock) a moving cluster that exists for a duration t and consists of more than `n` entities (`t` and `n` are application specific and could be applied to different sensor modalities). Three types of detections were used:

- Daily events - Which compares each day with all the other days within the selected dates;
- Weekday events – Which compares each day with only the same weekdays days from other weeks;
- Hourly events - Which displays the number of events within 15 minute intervals for each day.

$$t(P) = E(PX) + \sigma(PX) * p$$

$$f(Pi) = \begin{cases} 1, & i \geq t(P) \\ 0, & i < t(P) \end{cases} \qquad (1)$$

$$ds(X_i) = \frac{X_i - W_{li-1}}{\sigma(W_{li}) + X_i} \qquad (2)$$

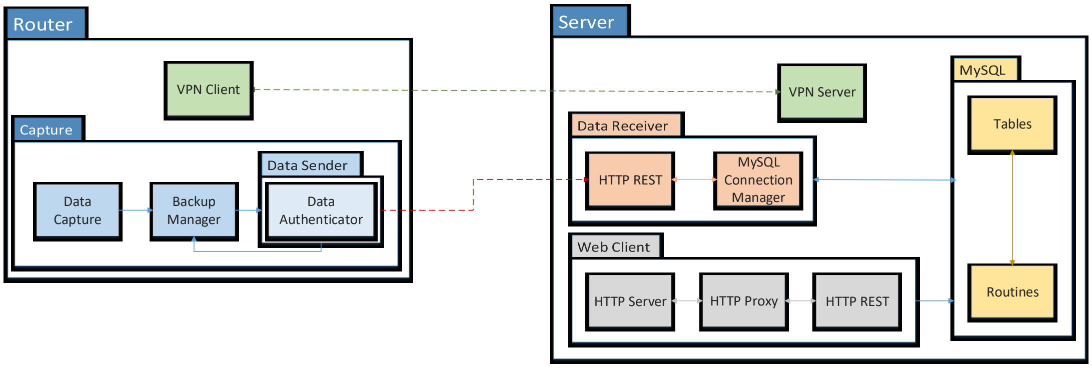

Figure 1 - System Architecture

Both the formulas (Equations 1 and 2) for the daily, weekday and hourly events, are based on event detection literature [12], which relies on a threshold method, that is defined accordingly to the sum of the average and the standard deviation for the selected population (days).

For daily and weekly events (Equation 1), the p value influences the distance threshold, between a value and the average (measured in the amount of standard deviations) in a specific place (P). When each value is compared against the calculated threshold (t), it is classified as an event (or not). This formula is based on a simple threshold, where the main purpose is to have a function for the threshold depending on the standard deviation and average, thus making the threshold automatic for every location based on the defined value of t.

The formula used for the hourly events (Equation 2) uses a window thresholding, with a dimension output. The window length and the ds function returns a number which, when compared against a defined thresholding value, gives us the likelihood of an event.

DATA VISUALIZATIONS

In Figure 2, we present some screenshots of the web-based interactive user interface that was created to enable the stakeholders and the local communities to get different visualizations and filters of the data being collected. The created interactive interface is able to make sense to the gather data, presenting complex information in intuitive and easily to understand ways. In particular, in Figure 2.1, we provide a map with the POIs, which show the most active points at the moment, alongside with the strength of the connections between the selected place and the others. It also enables the users to see the most common paths taken by people that cross the selected place. In Figure 2.2 we contrast the occupancy rate along the days of the week and hours of the day in the form of a heat map. Instead, the visualization in Figure 2.3 is centered in a selected POI and provides a quick glance to see the top 5 places where people come from and to where people go to from there. The platform also provides a dynamic chord diagram to display similar information about the movements as shown in 1), but in an abstract way, hiding the geographical distances between POIs, as displayed in Figure 2.4. In Figure 2.5 we provide an example of daily counts of people for each location. The data is also enriched with the display of the visitor counts as grey. Finally, Figure 2.6 represents a spline graph, where we show the average device count in the different places, spread by the hours of the day between a chosen date interval. It allows the user to select multiple POIs at the same time for comparisons between them.

RESULTS

In this section, we present the results of our analysis of the dataset, corresponding to the three main findings that emerged from the analysis of the dataset.

Finding #1 Passive Wi-Fi tracking is an accurate method for estimating flows of people in POIs

In our dataset we collected ground truth from several POIs, in particular the airport and port which kindly provided passenger counts for different periods of time. These passenger counts where correlated with the number of devices detected in the same days.

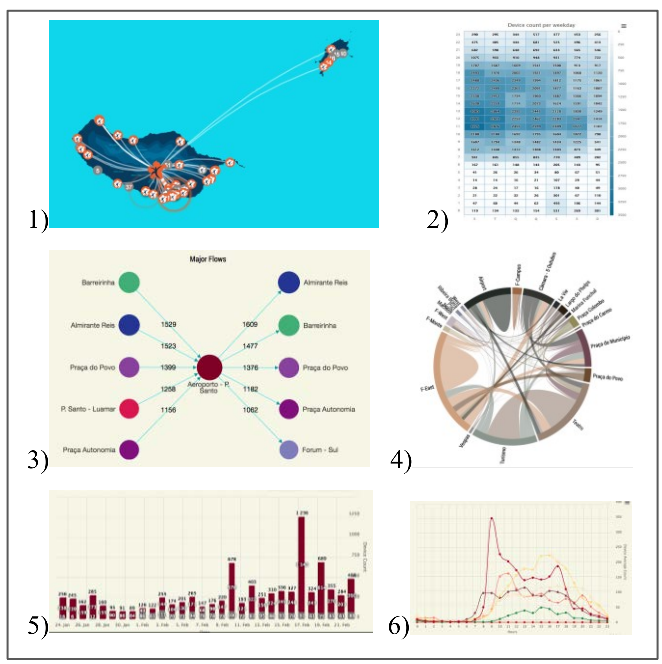

Figure 2 – Beanstalk Website Data Visualizations

Table 1 - Correlation between passenger counts and detected Wi-Fi devices at the airport and cruise terminal

POI	Days	Total cases (GT)	Total cases (sensed)	Pearson Correlation r= (p<0,05)
Airport	1-16 Jan	26 293	12 478	0,977
Arrivals	1-10 Feb	32 401	17 396	0,986
	1-10 Mar	34 360	17 707	0,980
	1-10 Apr	43 433	21 358	0,942
Airport	1-16 Jan	37 245	20 584	0,884
Departures	1-10 Feb	29 770	14 794	0,708
	1-10 Mar	32 493	13 902	0,930
	1-10 Apr	36 686	15 126	0,985
Port	1-31 Mar	84 281	14 605	0,574
Cruise ship terminal	2-30 Apr	98 293	19 463	0,623
Port	2-31 Jul	103 104	19 571	0,808
Ferry terminal	1-11 Ago	45 690	8 833	0,787
Google Popular Times				
Curral	Week days	-	31 948	0,684
La Vie		-	547 360	0,904
Machico		-	288 155	0,861
Monte		-	211 123	0,866
Teatro		-	1 081 147	0,635

Table 1 shows the results of the Pearson correlation tests performed with the daily device counts at the Airport (arrivals and departures) and at the Port (cruise ship and ferry terminals). It also shows the correlation of Google Popular Times graphs and average weekday counts of four popular sites covered by both Google and our platform.

The results in Table 1 show a strong correlation between the total number of people passing through the port and airport terminals and the numbers of devices detected. In our analysis, we are excluding random devices as our tests have showed the same device generating multiple random IDs in a limited time span (minutes). Correlation is obviously stronger in more controlled environments (airport departures) and less in open environments (port terminals). The same applies for the ratio of people vs. detected devices which is approximately 2 at the airport and more than 5 in the other POIs.

Finding #2 – Locals and tourists can be successfully differentiated using a passive Wi-Fi tracking

We also explored how the data could be used to differentiate visitors from locals. With the goal of finding out the types of users in each POI, we came up with a method to assess the number of visitors of the system. To accomplish this, we analyzed the age of the devices detection in the different POIs in the network. ted. We notice different distributions depending on the characteristics of the POI. Overall 47.1% of the devices are captured on the network only in one day (mostly randoms), the cumulative percentage goes up to 76.6% for devices found in the network for 8 days and a significant drop occurs at the 15 days period. We chose the 15 days of a device age in the system and its first appearance to differentiate a tourist from a local, ignoring the devices that only appear in one day.

Overall, during the 60-week period of this dataset, we detected approximately 1.8 million distinct devices (11 million including random MAC addresses), of these our system classified 11% as locals (≈ 200 000, when the official island population is roughly 260 000) and 36% as visitors (≈ 650 000) with the rest remaining unclassified (e.g only appeared once). Of the 36% visitors, the system classified 33% as visitors first detected at the airport, 20% in the city capital, 21% elsewhere, 8% at the cruise (port) and only (2% in the smaller Island of Porto Santo).

Finding #3 - Tracking information can be used to detect meaningful events such as arrivals, departures and gatherings of people

To assess this finding, in Table 2 we provide a summary of the evaluation of the event detection algorithms compared to the ground-truth obtained from the airport website. The results show a high accuracy of Wi-Fi event detection at the arrivals of the airport. With lower sensitivity (t=1,5) we have 69% of events matched leading to 88% of flight arrivals accurately detected.

It is important to notice that the detection of events is strictly related to the topologies of analyzed area. In other words, it is not surprising that in transit, generally crowded, small confined area (i.e. airport) it is easier to detect arrivals (due also to the building layout) instead of events in a street (e.g., the Carnival Parade in Funchal) which are easy to detect daily, but harder to sense in small periods of time. Regardless, in both the scenarios, our system provides evidence of the accuracy and effectiveness detecting meaningful events.

Table 1 – Summary of event detection accuracy at the airport

	Threshold	Total Flights	Total events	Events missed	Events matched	Matched/ Flights
Arrivals	1,5	5487	7015	12%	69%	88%
	1,6	5487	6406	19%	70%	81%
	1,7	5487	5742	26%	70%	74%
	1,8	5487	5089	33%	72%	67%
	1,9	5487	4368	42%	73%	58%

DISCUSSION

The first obvious concern about studies using passive Wi-Fi is related to privacy and commercial use of collected information with prior consent from the users. Our system was built for research purposes and implements a cryptographic hash function to prevent central storage of MAC addresses which could lead to potential privacy leaks. However, the technology for implementing similar systems is simple, relatively inexpensive and available for both commercial and personal tracking. Current strategies to protect privacy using MAC address randomization are getting traction by many vendors. However, as reported by [16] MAC address randomization alone is not enough to protect users' privacy since strategies can be used to explore information elements contained in probe requests.

CONCLUSION

In this paper we present Beanstalk, an interactive web platform able to perform and visualize systematic analysis of mobility patterns of tourists at their destinations. The approach takes advantage of a combination of based passive Wi-Fi tracking and ground truth data provided by tourism authorities. By analyzing a large dataset collected in Madeira, a medium sized European Island, we provide evidence of the accuracy and effectiveness of this low-cost method in inferring topological characteristics of tourist behavior and relevant typologies of trip itineraries. Through a case study focusing on the development and deployment of a passive Wi-Fi tracking system we explored the possibility of providing a wider community of stakeholders with information about spatio-temporal patterns of the movement of people in touristic destinations. This information lead to the confirmation of three findings: i) passive Wi-Fi tracking is an accurate method for estimating flows of people in POIs; ii) locals and tourists can be successfully differentiated using a passive Wi-Fi tracking; and iii) tracking information can be used to detect meaningful events such as arrivals, departures and gatherings of people.

Our work keeps expanding. The final deployment will include more than 100 POIs, corresponding not only to popular urban areas and landmarks, but also to more remote areas in the Laurisilva forest. We are also integrating other technologies in the routers to bring information about environmental, as weather, air quality and other parameters that communities and the stakeholders share interest in, and planning into evolving Beanstalk in a community network fully capable of offering other services to locals and tourists.

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