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Analyzing Carsharing “Public” (Scraped) Data to Study Urban Traffic Patterns

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Abstract

During the second half of the twentieth century pollution became a relevant problem, but after the seventies many governments began legislating against emissions. From then on, air pollution decreased as new technologies replaced older ones and now transportation, both private and public, is no longer the main source of pollution in modern countries (it still is in third world areas). Today **urban traffic** *per se* is the main problem. The pollution traffic component being relegated in the background, many governments and local administrations address the “congestion factor” by introducing regulations to reduce private traffic, considered the main source of congestion: access tolls and (public transport/car pools) dedicated lanes and odd measures such as narrowing lanes (and/or reducing their number), lowering speed limits, reducing parking availability, etc. Geolocation and road navigation technologies, combined with widespread mobile connectivity infrastructures have enabled researchers to study the evolution of traffic at a great depth. To the extent that some vendor, namely TomTom, uses collected customer navigators’ data to publish annual reports - the “TomTom Traffic Index” - about the state of congestion in major cities around the world. One **proposed solution** to congestion or, better, to the underusage of private vehicles, is the so called “carsharing”, i.e., pools of vehicles to be rented for short periods of time (minutes, hours), usually at higher costs (per day) than standard car rental prices. In many urban areas, such as Milan, where the authors live, measures against congestion are combinedly applied, e.g., tolls to enter a particular area, carsharing (with access to the paying area included), dedicated lanes, ban for certain types (older ones) of vehicles. Carsharing vendors “publish” (not entirely/easily accessible) data about the state of their vehicle pool... **Can this data be used to analyze these services’ effect, efficiency, usefulness, social cost, etc.?** The authors scraped carsharing vendors’ websites for a year, made this huge amount of data uniform, fed it into a mongodb database and then “played” with queries and graphed results. An interesting finding is that even on the carsharing pool a “lung effect” (people moving-in in the morning, moving-out in the evening) is evident, i.e., the common notion that carsharing is not for commuters can be argued. Another interesting behaviour is the evening peak usage, i.e., probably, caused by people using carsharing instead of taxicabs to go out at night (leisure). Moreover, the data show that vehicle usage (the total number of “busy” vehicles at any time) never goes beyond 70%, i.e., there is always a 30% pool of “free” vehicles. Throughout the paper interesting statistical data and graphs will be shown and discussed. Keywords: urban congestion, open data, public accountancy, pollution, anti-pollution policies, web scraping

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Figure 1 Historical trend of SO_2 (source: ARPA Lombardia)

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Keywords: urban congestion; open data; public accountancy; pollution; anti-pollution policies; web scraping

1. Introduction

Air pollution started to become a problem for human beings with the industrial revolution [10, 5, 11]. After the seventies many governments started to legislate [16] to try and reduce industrial (plants, materials, transportation, power generation, etc.) emissions. From then on, air pollution slowly began to decrease as new generations of technologies replaced older ones (see Figure 1 and all the graphs retrievable from ARPA: http://www2.arpalombardia.it/qariafiles/varie/MI_SO2.png, just replace MI with other Lombardy zones and SO_2 with other pollutants).

Nowadays **urban traffic** per se is perceived to be the main problem of modern countries cities. The pollution traffic component being relegated in the background, many governments and local administrations are addressing the “congestion factor” by introducing regulations [17] to reduce private traffic, considered the main source of congestion, such as:

- Imposing **access tolls** for particularly private-car-crowded zones
- **Dedicate lanes** to public transport/car pools
- **Narrowing** the lanes (to make cars go slower)
- **Reducing the number of lanes** to “disencourage” (by actually increasing congestion!) Car owners and push them towards public transport
- **Lowering speed limits** (again, “disencourage”)
- **Reducing parking availability** (again, “disencourage”)

Alongside these “barring” initiatives, a few years ago vendors started providing the so called “carsharing”, i.e., pools of shared (among many users) vehicles to be rented for short periods of time (minutes, hours), usually at higher costs (per day) than standard car rental prices. The rationale behind carsharing is that: 1) parking space is saved since a single parked vehicle serves a lot of users, not a single one (as is the case of a private car); 2) since it costs per use more than a private car (but less than a taxicab), many users, even if subscribed to the service, would use it wisely (maybe mixing it with standard public trans- port), thus reducing the overall car mileage load on the city; 3) it may help in further pollution lowering [3]. In many urban areas, such as Milan, where the authors live, measures against congestion are combinedly applied, e.g., tolls to enter a particular area, carsharing (with access to the paying area included), dedicated lanes, ban for certain types (older ones) of vehicles.

First carsharing systems were confined to designated spots in town where a user could take out and give back a car. Nowadays geolocation and road navigation technologies, combined with widespread mobile connectivity infrastructures have enabled vendors to let users leave (and find) cars wherever they want. Geolocation and navigation applications in general (i.e., not necessarily related to carsharing) let "market players" study users behaviour to the extent that some vendor, namely TomTom, uses collected customer navigators' data to publish annual reports - the "TomTom Traffic Index" - about the state of congestion in major cities around the world [8].

For carsharing, a smartphone application can track down the position of available cars and lead users to precise parking locations. Location data is, of course, stored and secured into vendors' systems... but some data is nonetheless available on the web because smartphone apps must get at least the geolocated list of available cars.

Can this data be used to analyze these services' effect, efficiency, usefulness, social cost, etc.? This paper represents an affirmative answer and shows the initial findings of a 1-year effort in carsharing data gathering undertaken by the authors.

A similar work has been described in [7], but in that case the focus was different: they wanted to identify class of users and they had access to the internal and complete carsharing vendor database. The work described here is instead based solely on data obtainable **without** directly asking the vendor. Statistical analyses presented here represent mass behaviour, or single car behaviour but decoupled from the user driving it.

1.1. Carsharing Systems in Milan (Italy)

In Milan, currently five (minus one who went bankrupt in 2015) carsharing vendors are available (see Section 2 for complete list and URLs). They are all similar in how they offer their service: 1) a user must subscribe to the service, for an annual fee (< 100 euro, for some vendor is 0, some include usage minutes as a "welcome package"); 2) the newly subscribed user must download and install a specific smartphone application (usually Apple or Android, not easy to find support for other operating environments); 3) the application works using GPS (no privacy) and mobile data (possible added fees); 4) the user needing a car can find it on the application real-time updated map and can even pre- book it (at a cost per minute); 5) {the above two operations can be done via callcenter, i.e. without the need for an "app", often with some added cost}; 6) the user approaches the booked car and he opens it with a RFID (Radio Frequency IDentification) smartcard or the phone itself (through NFC - Near Field Communication - or RPC - Remote Procedure Call); 7) the car can be started and used at will (usually within time/space limits, e.g. 50km); 8) when finished, i.e., parked, the user communicates the "end of service" through the app (or callcenter). Usage fees are usually by the minute: in the neighborhood of 25 eurocents per minute (i.e., 15 euro/h). Some vendor offers combinations and packages (blocks of minutes per month, etc.). As a comparison, taxicab fees (http://taxiblu.it/cms/tariffe-taxi/) are by km (~ 1 euro/km) or hour (~ 28 euro/h) plus an initial fee (between 3.3 euro and 6.5 euro). Carsharing users do not have to pay the AreaC (see Section 1.3) toll to enter the city center. Vendors pay forfaits (about 1100 euro/year per vehicle) to the Milan City Council and then they spread this cost over their users.

1.2. Opendata, "Obtorto Collo" Data and webscraping

Open data and content can be freely used, modified, and shared by anyone for any purpose [from: http://opendefinition.org/]

Publicity is justly commended as a remedy for social and industrial diseases. Sunlight is said to be the best of disinfectants; electric light the most efficient policeman [attributed to Justice Louis D. Brandeis (1856-1941)]

Opendata, in its wide meaning, is a political movement that pushes governments, firms, public administrations, etc. towards information transparency. According to this movement organizational entities, above all the public funded ones, should publish information about their internal workings. Info such as expenses, people roles, public activities, law making workflow (i.e., not only the final "product", the laws), public utility structures (e.g., bus stop locations, public offices timetables, ...) and commercial info (e.g., geolocated lists of firms/shops/etc. per type). When available, opendata is usually accessible via websites. Many organizations even dedicate entire websites to opendata only (e.g., data.gov USA, data.gov.uk UK, dati.gov.it Italy), instead of embed- ding an opendata section into their websites. Opendata has been categorized into classes based on format and licence [1] and on wider functional aspects [2]. Sometimes opendata is downloadable in batch (big compressed files) and sometimes it's accessible through API (Application Programming Interface). In, luckily rare, cases organizations do publish data that can be defined "open", but they also apply some so called "webstacles" (web obstacles) to reduce the usability for the public. In this latter cases a technique called “web scraping” (programmatively accessing data meant for humans on standard web pages) can be usefully applied [14] to obtain data “obtorto collo” (latin for “unwillingly”).

1.3. “AreaC” city center toll

“AreaC” is a (London Congestion Charge inspired) central zone of Milan in which vehicles are “regulated”: some are permanently banned (older ones, without exceptions, not even antique cars), some can enter for free (electric/hybrid/LPG cars, motorbikes and mopeds) and the rest must pay a toll. It is active Monday to Friday from 7:30AM to 7:30PM (6PM on Thursday). Cost is 5 euro for a single day, 2 euro for residents (limited to 40 tickets), discounts available if public parking is bought combinedly. While the Milan Town Council asserted that “AreaC” contributed to pollution reduction without publishing verifiable third party data, the Transport for London had already concluded [13] that no useful reduction had been obtained in London. Moreover, an independent [15] analysis based on ARPA - the Italian EPA - public data confirms this negative conclusion in the Milan context. TomTom defines the “congestion factor” as the difference (measured through a ratio) in overall speed between the worst time and the best time, i.e., it does not measure the absolute congestion in a city. Nonetheless TomTom publishes a ranking comparing world cities. As for Milan, TomTom index [8] claims a small reduction: [2008 → 33%], [2009 → 33%], [2010 → 33%], [2011 → 31%], [2012 → 28%] (“AreaC” introduction in Jan), [2013 → 28%], [2014 → 29%]. I.e., a 3% decrease (ignoring a possible trend from 2010). Moreover, nothing can be said about the events and causes for this change: it could be that the best time-of-day had worsened or vice versa.

2. Main text

In Milan (ITALY) there are five carsharing vendors: 1) Share’NGo (http://www.sharengo.it); 2) TwistCar (http://twistcar.it, discontinued since 17-nov-2015); 3) Enjoy (http://enjoy.eni.com); 4) Car2Go (http://www.car2go.com); 5) GuidaMi (http://www.guidami.net).

GuidaMi (now GirACI) does not publish data about cars, but it is a smaller contender in the carsharing universe in Milan. GuidaMi offers a very limited set of cars that must be taken and given back from few specified car parks in town. The other vendors do publish data about car positions and availability, some of them (Car2go) even offer API (Application Programming Interface) to query data, albeit with some limitations (low query frequency, need for a security key). To ease programming work the authors decided to simply scrape website data, using wget [4] in shell scripts or small python [9] programs periodically run on a always-on machine. These scripts run every minute, they save data in CSV (Comma Separated Values) or directly into a mongodb [6] database. All the data in CSV files is eventually fed into the same database.

These are the URLs (Uniform Resource Locators) used to get car status data: 1) Share’NGo (http://www.sharengo.it/core/publiccars); 2) Twist- Car (http://www.twistcar.it/start_twist.js); 3) Enjoy (http://enjoy.eni.com/ajax/retrieve_vehicles); 4) Car2Go (http://www.car2go.com/api/
v2.1/vehicles?loc=milano&oauth_consumer_key=car2gowebsite&format=json).

Scraped data, depending on the vendor, can be in the form of ready data (e.g. JSON, JavaScript Object Notation or XML, eXtensible Markup Language) that just need to be converted (parser libraries are readily available) into a suitable structure for the database, or it can be gathered in the form of an HTML (Hy- perText Markup Language) page that must be processed to extract structured data. In the latter case filters such as html2text, cut, grep, sed, awk, etc. (typical GNU/Linux commands) must be combined to extract the interesting data from the formatting HTML metadata. The data available (after scraping and cleaning) from the vendors is described by the following:

Share’NGo: active, battery, busy, charging, damages, extCleanliness, firmware- Version, frame, hidden, imei, intCleanliness, isReservedByCurrentUser, km, label, lastContact, lastLocationTime, latitude, location, longitude, mac, manu- factures, model, notes, obcInUse, obcWlSize, parking, plate, rpm, running, soc, softwareVersion, speed, status, vin

TwistCar: licensePlate, fuelLevel, insideStatus, outsiteStatus

Enjoy: car name, car plate, fuel, latitude, longitude, address, virtual rental type id, virtual rental id, car category type id, car category id, on click disabled, car model data

Car2Go: address, coordinates(lat,long), engine type, exterior condition, internal condition, car name, need smartphone, vehicle id

A record represents the current status of a car. As the reader can see, the Share'NGo vendor is the most verbose, albeit not every field is useful since the data is available on web only when the car is parked, i.e., fields such as speed is always zero when scraped.

The sampling frequency is 1/min, i.e., website data is scraped every minute generating 24h∗60m/h = 1440 samples per day. When the system was designed, it was foreseeable that the shortest rent would be at least a few minutes (thus sampling at 1 minute intervals could be considered oversampling), but that minimum use case was an assumption the authors wanted to verify examining the actual data by finding repeated records.

The heterogeneous gathered data is then intersected into the following mon- godb document schema: id = identifier, engine = type of engine (electric, gasoline, etc.), car plate = plate, service name = vendor (Enjoy, Twist, etc.), latitude = position latitude, longitude = position longitude, date = ISO date (of sample), fuel = fuel level %. Over this database the authors created queries to extract information and generate the graphs shown in Section 3..

3. Analysis

In the following subsections two analyses (usage and average distance) are shown and commented. They are based on data gathered between September and March 2016.

The authors applied a straightforward methodology to extract the first findings on the data, i.e., for every aspect under investigation they: generated general statistics (min, max, average, quantiles, etc.) and created plots for every day, to look for evident patterns, if any.

Luckily, from the authors' point of view, the graphs showed an evident daily and weekly patterns (see Figure 2, 3 for an example), such as:

- Every day is "cyclical", e.g., night differs from day, office hours represent peaks, etc.
- There are "seasonal" (weekly) effects: a) days from Monday to Friday are similar to one another; b) Saturday and Sunday are similar; c) Saturday and Sunday differs from Mon-Fri workdays
- There are, of course, random fluctuations

To better analyze the in-week patterns a more thorough statistical inspection was carried on. Data were divided into weeks and for every week Q-Q plots were created. The Q-Q (Quantile-Quantile) plots are used to compare if two samples are "statistically similar". A Q-Q plot for every day pair (Mon-Tue, Mon-Wed, Mon-Thu, etc.) in every week was generated, originating $\binom{7}{2} = 21$ Q-Q plots per week (examples in Figure 5 and Figure 8). This procedure statistically confirmed the evident pattern difference between Monday-Friday and Saturday and Sunday.

Some abbreviations used in the rest of this paper: H = Holiday; NH = Non Holiday; stats = computation of Minimum, 1st Quantile, Median, Mean, 3rd Quantile, Maximum; fivenum = computation of Minimum, Lower-hinge, Median, Upper-hinge, Maximum. Data analysis was carried on using R [12].

3.1. Cars usage

Let's define the function:

$$Car\ Available_i(t) = \begin{cases} 1, if\ parked\ (i.e. available) \\ 0, otherwise\ in\ use \end{cases} \quad (1)$$

modeling the availability of a single car at a given time t, the function returns 1 ("true") if the car is free to be booked by a customer. Then the total number of free cars at a given time t is:

$$CarsAvailable(t) = \sum_{i \in Cars} CarsAvailable_i(t) \quad (2)$$

When this value is low it means that many cars are “taken”, i.e., are in use. In Figure 2 (Mon-Fri) and Figure 3 (Sat-Sun) is represented a typical week usage, other weeks in the data are similar to the one shown.

Notable remarks in Figure 2 (Mon-Fri) are the following:

1) Night-time (between 2AM and 7AM) represents a peak of free cars;
2) The usage peak (least number of free cars) is between 6PM and 9PM;
3) Morning (between 8AM and noon) usage is lesser than afternoon (noon to 7PM) usage.

Notable remarks in Figure 3 (Sat and Sun) are the following:

1) Night-time peak sports a shorter timespan (between 6AM and 8AM) w.r.t. the Monday-to-Friday night-time peaks;
2) There is a usage peak between midnight and 2AM, often more substantial than the afternoon peak.

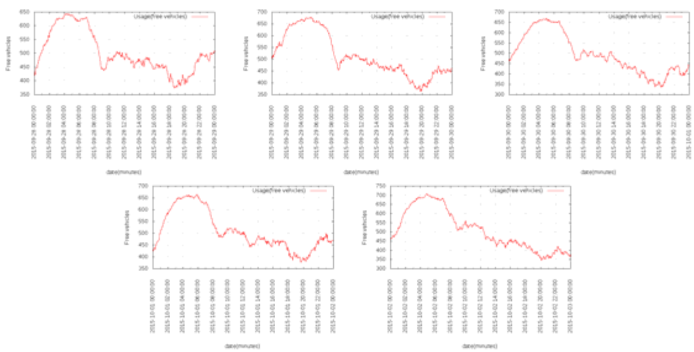

Figure 2Usage (# of free cars) average: a typical week (Mon-Fri)

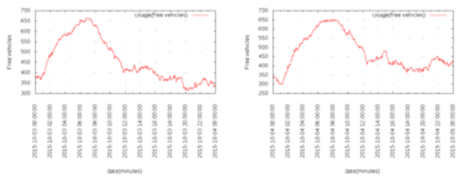

Figure 3: Usage (# of free cars) average: a typical week (sat-sun)

Table 1: Stats for week in Figure 2 and Figure 3 (free cars)

DAY	DATE	Min	1st Qu.	Median	Mean	3rd Qu.	Max
Monday	2015-09-28	374.0	452.0	483.0	503.1	561.0	644.0
Tuesday	2015-09-29	363.0	453.0	492.0	515.8	602.8	677.0
Wednesday	2015-09-30	336.0	427.0	484.0	496.2	571.8	670.0
Thursday	2015-10-01	375.0	456.2	484.0	508.8	574.0	664.0
Friday	2015-10-02	346.0	420.0	479.0	507.3	595.5	709.0
Saturday	2015-10-03	312.0	371.0	417.0	456.9	552.0	665.0
Sunday	2015-10-04	299.0	403.0	438.0	471.6	552.0	651.0

Table 1 shows the `stats` for the same week, to let the reader see the similarity between Mon-Fri days and the evident statistical difference from Mon-Fri and Saturday+Sunday.

Figure 4 shows a graph of the (partial) `stats` over the whole set of usage data, to visually follow the trend of (*min, mean, max*) along the timeframe from September to December 2015.

Figure 5 depicts the usage Q-Q plots of two day pairs taken as example: 2015- 10-05 against 2015-09-29 (Tue against Mon), near the $y = x$ line → statistically similar; 2015-11-22 against 2015-11-17 (Sun against Tue), far from the $y = x$ line → statistically different. I.e., users' behaviour on Sunday is different from a weekday.

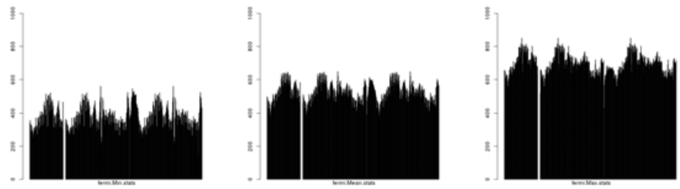

Figure 4: Graph of partial stats (Min, Mean, Max) on free cars [Aug 2015 → Mar 2016]

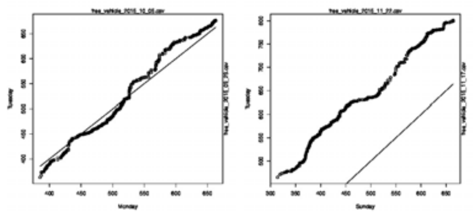

Figure 5: Usage Q-Q plots: typical NH-NH versus typical H-NH

3.2. Average distance from city center: the "lung" effect

In this Section we analyze the overall distance of cars from the city center. At any given time, *t*, the distance of a single car is defined by:

$$CarDistance_i(t) = |CarPosition_i(t) - CityCenterPosition| \tag{3}$$

I.e., the module of the vectorial distance between car and center (latitude, longitude).

Then we define the average distance at time *t* by:

$$AverageDistance(t) = \overline{CarDistance_i(t)}[i \in Cars] \quad (4)$$

I.e., we compute the average of all car distances from city center, at a given time.

Notable remarks in Figure 6 (Mon to Fri) are the following:

1) "lung" effect': average distance decreases during the day (8AM to 6PM) and increases during the rest of the day, i.e., people move into the city during day- time and move out of the city otherwise;
2) there is a concentration peak between 11AM and 2PM, i.e., during lunchtime users are (on the average) nearer to the city centre;
3) between 8AM and 11AM there is a sudden out-movement of people closely followed by an in-movement, i.e., many users move in & out in those hours, but not exactly at the same time (they would blend in the average distance);

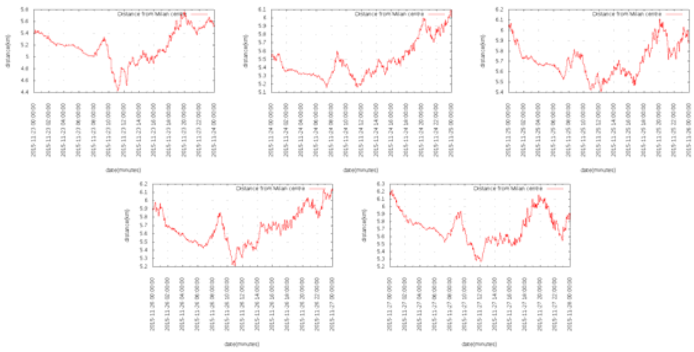

Figure 6: Average of distances: a typical week (Mon-Fri)

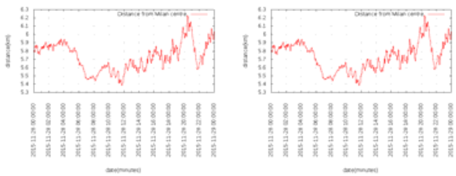

Figure 7: Average distances: a typical week (sat-sun)

4) (also comparing Figure 7) during Mon-Fri night & mornings (midnight to 6AM) average distance decreases faster than during Sat-Sun.

A **notable remark** in Figure 7 is that between 8AM and 8PM there are no big spikes, but only a general and slow increase in average distance.

DAY	DATE	Minimum	Lower-hinge	Median	Upper-hinge	Maximum
Monday	2015-11-23	4.421603	5.015418	5.192918	5.408927	5.764844
Tuesday	2015-11-24	5.158726	5.324029	5.421478	5.596359	6.091165
Wednesday	2015-11-25	5.405926	5.593709	5.686358	5.810312	6.109080
Thursday	2015-11-26	5.211782	5.504981	5.665719	5.832572	6.149302
Friday	2015-11-27	5.270121	5.568415	5.711816	5.862285	6.221498
Saturday	2015-11-28	5.386509	5.596878	5.742660	5.855843	6.229547
Sunday	2015-11-29	5.400850	5.592309	5.719909	5.866767	6.246429

Table 2: Fivenum for week in Figure 6 and Figure 7

Table 2 shows the fivenum for the same week, to let the reader evaluate the similarities and differences. There is a lower distance peak on Monday and then a slow increase during the week.

Figure 8 depicts the distances Q-Q plots of two day pairs taken as example: 2015-10-22 against 2015-10-21 (Wed against Thu), near the y = x line → statistically similar; 2015-11-15 against 2015-11-16 (Mon against Sun), far from the y = x line → statistically different. I.e., again, users' behaviour on Sunday is different from a normal weekday.

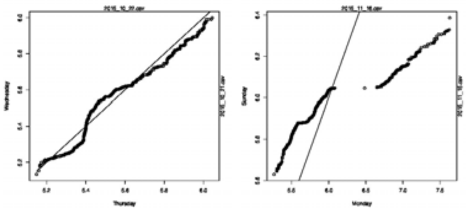

Figure 8: Distances Q-Q plots: typical NH-NH versus typical H-NH

4. Conclusions and future work

This paper describes a yearlong effort in web scraping and analyzing car- sharing data in Milan, Italy. Since August 2015, shell and python scripts run every minute to collect data from carsharing vendor websites, then data is uniformed and fed into a mongodb database. Stats and graphs are then generated from the database. Such a dataset can be enormously useful to stakeholders (citizens, potential carsharing competitors, public administrations) interested in understanding mobility trends and in designing new sustainable mobility services. Current vendors should make their data more easily available for the sake of public good.

Data gathered&plotted so far, presented in Section 3, shows that:

1) there is an evident usage pattern (in # of free cars and average distance from center) difference between work days (Mon-Fri) and weekends (Sat-Sun);
2) there are interesting time windows (Fri and Sat nights, morning 6AM-9AM, morning 8AM-noon, 11AM-2PM, etc.) that could be more thoroughly analyzed;
3) there are usage peaks outside the "AreaC" time window;
4) the average distance from center stats (on Aug 2015→Mar 2016 data) are: Min.=3.953, 1st Qu.=5.452, Median=5.664, Mean=5.674, 3rd Qu.=5.872, Max.=9.570; Milan radius can be approximated with sqrt(181.67Km2/π) = ~ 7.6 Km i.e., the average distance is centered at 73% of city radius.

The authors are currently analyzing:

- "hot spots" (zones where cars are more frequently left);
- movement trends (extracting trip vectors for every vehicle);
- frequency and location of fuel refilling.

While future and more general analysis work can be imagined, such as: studying congestion zones and times (e.g., to identify badly mobility-wise de- signed urban zones), correlating carsharing data with other data (public trans- port, weather, holidays, strikes, etc.), evaluation of carsharing vendors' quality of service (in terms of covered zones, vehicle availability, etc.), comparison with similar studies undertaken worldwide.

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