Hybrid Human Machine workflows for mobility management

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ABSTRACT

Sustainable mobility is one of the main goals of both European and United Nations plans for 2030. The concept of Smart Cities has arisen as a way to achieve this goal by leveraging IoT interconnected devices to collect and analyse large quantities of data. However, several works have pointed out the importance of including the human factor, and in particular, citizens, to make sense of the collected data and ensure their engagement along the data value chain. This paper presents the design and implementation of two end-to-end hybrid human-machine workflows for solving two mobility problems: modal split estimation, and mapping mobility infrastructure. For modal split, we combine the use of i-Log, an app to collect data and interact with citizens, with reinforcement learning classifiers to continuously improve the accuracy of the classification, aiming at reducing the required interactions from citizens. For mobility infrastructure, we developed a system that uses remote crowdworkers to explore the city looking for Points of Interest, that is more scalable than sending agents on the field. Crowdsourced maps are then fused with existing maps (if available) to create a final map that then is validated on the field by citizens engaged through the i-Log app.

CCS CONCEPTS

• **Human-centered computing → Collaborative and social computing**; **Ubiquitous and mobile computing systems and tools**; • **Applied computing → Transportation**.

KEYWORDS

modal split, map generation, hybrid workflows, crowdsourcing

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1 INTRODUCTION

The transport sector accounts for 4% of EU's GDP and 9M jobs [17]. The European Commission has outlined congestion, oil dependency, greenhouse gas emissions, and infrastructure quality as major challenges to overcome towards achieving sustainable mobility. From a global perspective, the UN 2030 development agenda specifies as its 11th Sustainable Development Goal (SDG), the provision of "access to safe, affordable, accessible, and sustainable transport systems for all"[1].

A pathway to achieve these goals taken by many cities has being to become *Smart* [1], i.e., take advantage of the connectivity enabled by 4G infrastructure, the ever-decreasing cost of sensors and IoT devices to monitor environmental variables. However, after collecting such large amounts of data, it is of capital importance to (i) ensure that the it *makes sense* for the services that citizens expect to get from the city; and (ii) that citizens are engaged in the process. After all, in many situations, the required data is theirs (their trips, their transport choices, etc.), and only them can provide updates and or corrections. Furthermore, several works have pointed out the importance of supporting citizens in an active role along the whole data value chain [2, 7].

In this paper, we present the design of two end-to-end hybrid human-machine solutions to real mobility problems that municipalities face: the estimation of modal split, and the generation and maintenance of maps of urban mobility infrastructure. The solutions were developed in the context of the EU H2020 project

[1]http://www.slocat.net/sdg-targets

QROWD[13] based on requirements elicited by the Trento Municipality (A partner of the consortium). Modal split is an indicator of the percentage of people that chooses which transportation mode. It is particularly important since it gives a clear picture of how citizens move and commute, and is the first step towards the informed development of transport policies. It is traditionally computed through paper of telephone surveys, in an expensive, time consuming, and non-scalable way. On the other hand, mobility infrastructure maps are important for powering sustainable mobility services, e.g., knowing where bike racks are and their capacity, enable routing services to propose the use of bike, encouraging the reduction of greenhouse emissions. However, for different reasons (infrastructure not owned by the council, digitalisation errors), it is often the case that municipalities don't have that information, and sending municipality employees to scout all the city is expensive.

The remainder of the paper is structured as follows. Section 2 describes i-Log, the mobile application that we use to both collect data from citizens and to interact with them in both hybrid workflows. Section 3 describes the design of the hybrid workflow for mapping mobility infrastructure, and the components that comprise it. Section 4 describes the design of the hybrid workflow for modal split estimation, and the components that comprise it. Finally, section 5 concludes the paper.

2 THE I-LOG MOBILE APPLICATION

How mobile devices can empower users is a relevant topic in areas such as crowdsensing and crowdsourcing [4, 18]. Their unique features make smartphones and wearables the ideal tool for crowdsourcing experiments that require to tap into the wisdom of the crowd and exploiting their knowledge. The general idea is to leverage the power of those devices that are already owned by the citizens, while at the same time balancing the level of intrusiveness of the solutions, to ensure a high rate of response and not hurting the relationship between citizens and public administrations.

With this in mind, the University of Trento developed a mobile application called i-Log [19], which collects data from the user in an unobtrusive, GDPR compliant and efficient way. The application can be used to generate two very diverse types of data, namely (1) streams of value-pairs generated by the devices's internal sensors, while (2) it can also collect the user input in different formats, from text to visual. In crowdsourcing this human knowledge is often provided as annotations or labeling of data collected via sensors [8]. This type of human contribution is at the heart of the "human in the loop paradigm"[2] which leverages both human and machine intelligence to create hybrid machine learning models by involving humans in training, tuning and testing data for a particular machine learning algorithm. The final goal is to use humans to improve the quality of the results of the machine. Specifically, the idea is that every user should provide her own annotations and contributions, that are aware of the context and thus are more meaningful and accurate [3, 6].

A simplified version of i-Log's architecture is presented in Figure 1. The system is composed of a set of modular, logically isolated components, each one enabling a sub-set of the overall functionalities of the application. The modularity of the architecture allows to personalize the application and adapt it to different contexts and projects, with the need to modify only the involved components. This architecture gives i-Log a significant advantage in terms of adaptability and extendibility of its features. The four main components are:

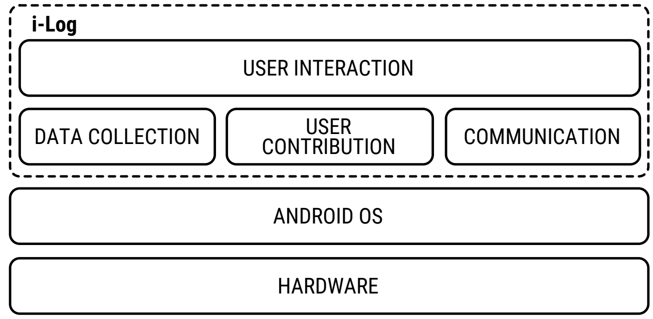

Figure 1: i-Log mobile application architecture.

- **Data collection module:** it is responsible for efficiently collecting and storing the data from the smartphone's internal sensors. The data collection has been designed to be remotely configurable in terms of (i) which sensors to use and (ii) at which frequency to collect data from them. In fact, due to the requirements of the individual projects we would need to enable some sensors while disabling others. This is true also from a GDPR perspective where the data minimization principle applies. Once collected, the data are temporarily stored in compressed and encrypted logs file on the device and synchronized over Wi-Fi whenever a connection is available.
- **User contribution module:** is responsible for collecting the user's knowledge in terms of answers to simple questions (a contribution). The knowledge can be of different types, from text, to images and to other objects that are use-case dependent, i.e., coordinates on a map. The questions are sent by a remote server as JSON objects that are then visualized on the smartphone and made available to the user.
- **Communication module:** is responsible for all the outbound and inbound connections. More in details, it allows to contact the backend infrastructure of the application to perform operations such as registering/logging in users, to synchronize the generated logs of data and save them in a database. At the same time, it allows to receive the questions that the user has to reply to provide her own knowledge and keep her in the loop.
- **User interface module:** i-Log's main functionality is to collect data about the user while running in background on the phone. The reason for this is that the collection process must be as less obtrusive as possible. For this reason the user interface is very limited: it consists on a notification system that is always present in the notification area of the smartphone while the data collection is active. This is a mandatory requirement from a GDPR point of view since the user must always been informed when someone is dealing with her data. A second notification is present whenever the user is

[2]https://www.figure-eight.com/resources/human-in-the-loop/

asked to provide his knowledge. From these two notifications the user can access the actual views of the application, two menus, Settings and Contributions that allow respectively to setup the application and to have access to all the contributions.

With respect to the QROWD project, i-Log is a pivotal tool to obtain data from citizens of the Municipality of Trento about real time information on traffic and multimodal transport and involve them to improve its mobility by enabling data-driven policy making by providing the users with an interface for harvesting crowdsourced data.

3 GENERATING MOBILITY INFRASTRUCTURE MAPS

An essential ingredient for the design and implementation of mobility policies is knowledge of the current infrastructure. Unfortunately, several public authorities lack such information, since it is expensive to generate, maintain and update, meaning that the location of strategic city items, such as bike racks or disabled parking spots, is unknown. In some cities, engaged communities of volunteers produce and share locations of Points of Interest (an approach studied in the Volunteered geographic information (VGI) field [16]), e.g., contributing to Open Street Maps. Unfortunately, since the participation in such communities is mainly voluntary, there is no control on what their contributions are, when they make them, and on which area of the city they will contribute. An alternative is to physically send municipality employees to locate the required items, however, this does not scale in the area of the city, as to be certain that all the city has been covered, and no items have been over-sighted, several employees need to be sent to the field.

Our solution to this problem combines the automated fusion of existing, possibly incomplete maps (if available), with two crowdsourcing tasks, as described in Figure 2. Our workflow is comprised of four phases: (1) crowdsourced **generation** of new maps (2) **acquisition** of pre-existing and new maps into a central repository, (3) automated **fusion** of the results of available maps to produce an interlinked map and finally, (4) **curation** of the results, using different crowdsourcing strategies.

3.1 Generation

To crowdsource map generation we designed a standalone tool called VCE (Virtual City Explorer). The VCE allows contributors to explore inside street-level imagery services (we used Google Street View[3] in our implementation), and report the coordinates of items that satisfy given requirements. Such contributors can be either citizen volunteers or paid crowdworkers recruited from external channels, e.g., from the traditional crowdsourcing platforms, such as Figure Eight[4] or Amazon Mechanical Turk[5].

The VCE accepts several parameters to control how the mapping is done. An end user, e.g. a municipality, defines the area that needs to be explored by the contributors and the type of infrastructure that wants contributors to locate. In the case of crowdworker contributors, an end user can set how many of them she would like

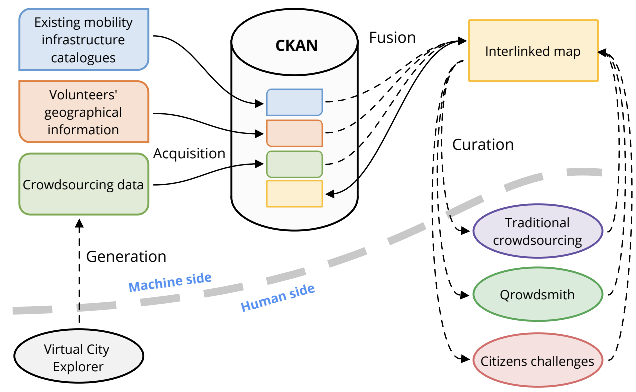

Figure 2: Hybrid workflow for mobility infrastructure mapping.

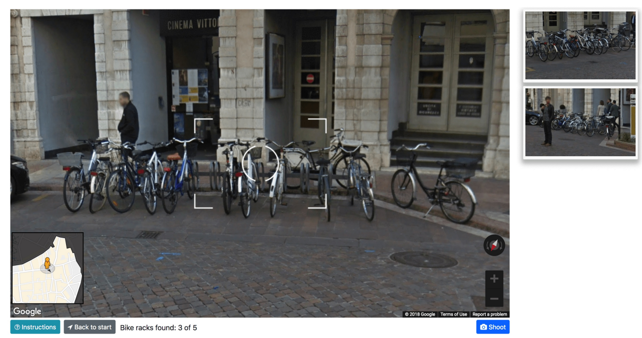

Figure 3: Interface of the VCE from the contributor perspective.

to assign to a given area. Otherwise, for volunteers, the link to the mapping task can be distributed to an arbitrary number of contributors. In this way, the VCE helps to overcome the main limitations of physical approaches, namely, the number of contributors and their direction to specific areas. In turn, the approach is limited to the existence and up-to-dateness of street-level imagery.

Figure 3 shows a screenshot the VCE interface from a contributor's perspective. Before exploration starts, the contributor reads the task instructions that explain its general functioning works and which are the types of objects required to locate. The contributor then starts her exploration from a random within the area of interest. When a contributor discovers a candidate item, she is required to take three photos of it, from three different angles. In the background, the VCE triangulates the vectors of the different angles to determinate the coordinates of the item and stores them in a database. After submitting a pre-established number of items, the task ends. In case a crowdworker was the one completing the task, is redirected to the crowdsourcing recruiting platform to receive her payment.

We evaluated the VCE for the task of generating bike rack maps in comparable areas in the cities of Trento and Washington, finding that contributors are effective locating mobility points of interest

[3] https://www.google.com/streetview/
[4] https://www.figure-eight.com/
[5] https://www.mturk.com/

Compare to sending an employee VCE, also resulting faster covering larger areas, and being less expensive. A separate paper [12] provides a thorough description of the VCE and its experimental evaluation.

3.2 Acquisition

The second phase of our hybrid workflow is data acquisition. In this phase, different maps of PoIs, possibly generated from different sources, are integrated to be used. Such datasets are usually built following different approaches, thus the data collected can have different nature, containing data in different formats and describing different properties (e.g., one approach can represent a bike rack as a geo-polygon, and other as a point). Furthermore, datasets could be updated an arbitrary number of times (e.g., a new execution of the VCE), creating the need of version management.

We use a combination of NiFi processes for data ingestion, and the CKAN open-source DMS (data management system)[6] to provide a centralise repository of datasets for the following phases.

3.3 Data Interlinking and Fusion

From the acquired datasets stored in the CKAN repository in the previous phase, the interlinking and fusion phase is run. First, the interlinking component has to infer which of the entities in the considered datasets refers to the same physical item. The result of the interlinking is a set of entity pairs, each associated with a similarity score (confidence value). This operation that could be performed with a naive approach, requiring computing similarity for all pairs of entities (cartesian product) is done in our interlinking component with *LIMES* [14], an interlinking engine that significantly improves performance by pruning comparisons. Using LIMES, we convert the source data to RDF, generate and derives URI for the PoIs collected in the previous step, and from any other available data source, and represent spatial information using GeoSPARQL. Based on the generated RDF, we use LIMES to generate links of *spatial proximity* among the coordinates of the PoIs, and between any other property, e.g., are they labeled as mobility items, are they popular items, etc. The interlinking phase is followed by the fusion one that concerns with obtaining a single coherent representation of an entity from multiple representations. We implement a clustering operation that first chooses representative identifiers based on the data source ranking and then merge the attributes needed for domain-specific conflict resolution. In the particular case of the city of Trento, we choose as representative the PoIs from data collected by a Muncipality employee, and tried to link to PoIs detected by citizens with i-Log. The result of the interlinking and fusion phases is a new dataset of static items generated through a smart aggregation of the previously available datasets. To verify the results, we use crodsourcing curation, as detailed in Sec. 3.4

3.4 Data curation

The output of the fusion phase is an unified dataset that established which of the mobility infrastructure items collected by different approaches are the same. The interlinking comes with a confidence value to estimate how sure it is that two items are the same. For items with low confidence values, it would be worth to require additional verification. We cal this phase data curation, and developed three human approaches to perform it: (1) by engaging citizens to go verify in place, and (2) recruiting crowdworkers or volunteers for a crowdsourcing task, (3) through a gamification approach that may be played either by crowdworkers or citizens, that can be seen as an extension to (2). The three approaches are detailed in the following three sections.

3.4.1 Citizen challenges. The first approach we can use as a confirmation of the interlinking output is to leverage directly on the citizens. A difference with respect to the other solutions is that the citizens need to physically go and check if a bike rack is still present or not. This can be considered an additional challenge with respect to a solution where a person can validate from her computer, but at the same time gives us additional confirmation, in real time and with the most up-to-date information. This type of data curation is made available through the i-Log application and its functionality that allows to present questions to the users. More in detail, the citizens can participate and contribute to *Challenges* made available by the Municipality of Trento (Fig. 4 (left)). Once they agreed to participate, they are presented with a map that highlights where the bike racks are located (from the interlinking step).

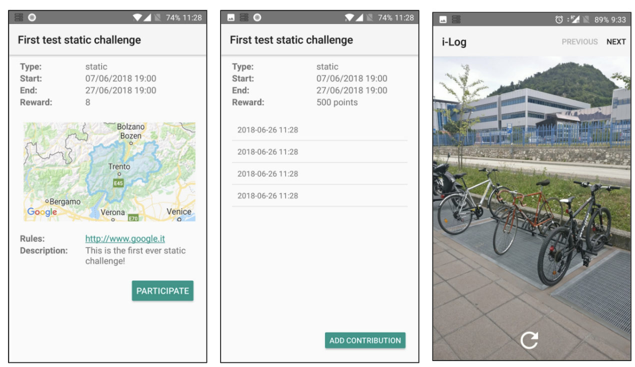

Figure 4: Three i-Log interfaces, for (left) a user to decide if accept to participate a challenge, (middle) a user contribute with a new item detection, and (right) a user taking a picture of a new item discovered.

The challenge consists in physically going to the designated points and confirm if the bike racks are really there. The confirmation occurs through what we call a *contribution* (Fig. 4 (center)) that consists in the following actions that the user has to take:

(1) Read the textual/visual instructions that are provided through the i-Log user interface. The message we were presenting is: *Hi! It seems that there is a bike rack here; is it true? If yes, before answering the questions on the bike rack, we would like to ask you if you could localize yourself, then take three nice picture of the bike rack itself. Please note that the photo should cover the whole bike rack!.*
(2) Localize her device through a dedicated procedure. It consists in a map view that gets the location from the GPS sensor and generates a pinpoint. The location is considered valid only if the attached accuracy is below $10.0m$.

[6] https://github.com/ckan/ckan

(3) Reply to a first textual question: *Is the bike rack still here?*. The available answers are Yes/No. If the selected answer is No, then the contribution is considered finished.
(4) Take a picture of the bike rack. The location from the GPS sensor is also collected at this point 4 (right)).
(5) Take a second picture in a position different from the first one.
(6) Take a third picture in a position different from the first two.
(7) Reply to a textual question: *What kind of bike rack do you see?*. In this case the answers are three pictures of three different types of bike racks.
(8) Reply to a textual question: *How many spots does the bike rack have?*.
(9) Reply to a textual question: *How many available spots does the bike rack have?*.

Once a contribution has been generated, i-Log stores them locally before sending them to the backend once a Wi-Fi connection is available.

3.4.2 Traditional crowdsourcing. The second approach we can use to confirm the output of the interlinking component is through a simple crowdsourcing task to be carried out either by paid crowdworkers or volunteer contributors.

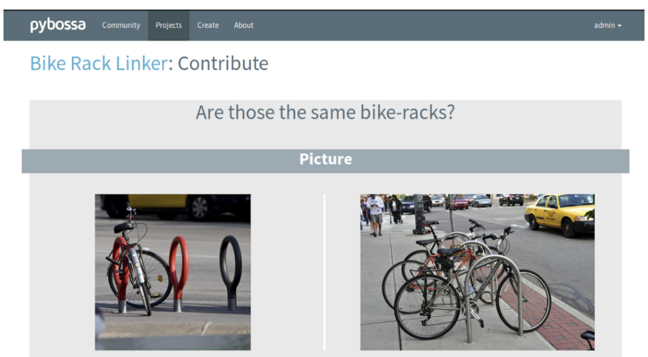

Figure 5: The data curation phase requires crowdworkers to carry out simple tasks, such as determining if the interlinking of two items from different dataset was performed correctly.

Fig. 5 shows, the interface of a task we designed to be run in Pybossa[7], a crowdsourcing framework to analyze or enrich data. The task requires contributors to confirm if the items pictured in two photos (bike racks in Fig. 5) correspond to the same item. .

3.4.3 Qrowdsmith. An extension to the previous approach is the use of gamification to better engage with contributors. The effort of creating a gamified environment for crowdsourcing contributors is justified by studies that demonstrate how hedonic motivation can be placed alongside the economic one to lead to better quality results, by improving the quality of the engagement of the contributors [5]. In this context, we developed Qrowdsmith, a standalone tool that makes use of gamification for engaging with contributors, either volunteers or paid crowdworkers recruited from traditional crowdsourcing platforms such as figure eight or Amazon Mechanical Turk. Qrowdsmith offers a series of gamified elements such as leaderboards, badges and levels to engage with crowdworkers providing them with feedback concerning the work done over time to favour the establishment of long-time relations with workers, that are even more motivated to return on the platform to increase their scores and climb the leader board. Fig 6 shows the interface of the main menu of Qrowdsmith: the crowdworker can choose among several available tasks, some of them to be carried out in the solo mode, other requiring participation of multiple users. Currently, Qrowdsmith is in a prototypal stage and supports three types of tasks, respectively: (i) *image tagging* where contributors are required to provide labels to describe the content of given pictures; (ii) *item comparision* that similarly to the task described for the Traditional crowdsourcing apprach (Sec. 3.4.2), requires workers to establish if two photos refer to the same item; and (iii) *item validation* where contributors are required to judge whether an item depicted on a photo conforms to the given guideline.

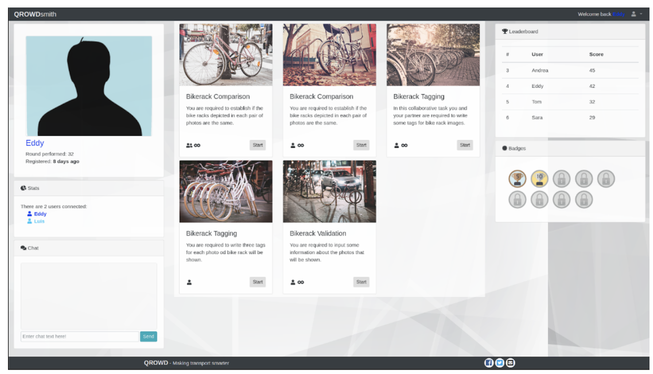

Figure 6: The interface of Qrowdsmith, where volunteers or paid contributors engage performing tasks in an environment having gamified elements, such as badges, leaderboards, and rewards.

4 MODAL SPLIT ESTIMATION

In this section we describe the hybrid workflow for estimating modal split[8] Figure 7 depicts the general schema of the solution. We follow approximately the same general pattern as described in [15]. The general idea is to use i-Log to collect raw sensor data about citizens movement, and compute as automatically as possible the trips and transport modes of the citizen. Citizens might be required to confirm the computed trips and their transport mode if the machine is not confident enough. This turns the lengthy and cumbersome process of filling a paper survey into just letting an app run in the background and occasionally answer some questions

The next sections details the main phases of the hybrid workflow for modal split: the personal data collection (Sec. 4.1), the

[7] https://pybossa.com/

[8] A demonstration of an earlier version of this workflow was presented in the Project Showcase Track of KDD'18. https://www.kdd.org/kdd2018/files/project-showcase/KDD18_paper_1810.pdf

trip inference 4.2, and finally the trip and segment confirmation (Sec. 4.3).

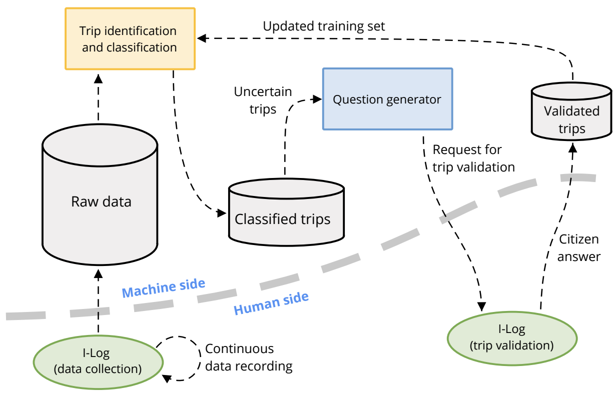

Figure 7: General schema of the workflow for the computation of the personal modal split.

4.1 Data collection from citizen devices

As explained in Section 2, the i-Log application can be used to collect personal big data from the mobile devices of the users. The fact that no dedicated device has to be used and, instead, the citizens can use their own device facilitates the exploitation of the tool in real life and in the wild, scenarios like the ones developed in the QROWD project. i-Log is a general purpose data collection tool that adapts to the specific need of the use case of each project. This is true for both the type of data it can collect, sensor data and user's contributions. The adaptation involves multiple dimensions: (1) the analysis of the privacy and ethical requirements, (2) the definition of the devices to collect data from, (3) the definition of the sensors on each device to collect data from and (4) the definition of how frequently to collect data from each sensor.

When dealing with people, it is of primary importance to take into consideration privacy and ethics. Each institution usually has a dedicated board that deals with such topics when humans are involved, and this happened also for the QROWD project. The outcome of the discussion is an installation procedure that is intended to present the user the *Informed Consent* about the data collection and explicitly ask her to *grant permissions* to collect data from those, more critical sensors from a privacy perspective, i.e., the GPS. The procedure guides the user through the process with images and text that explains the reasons for which the study needs the specific kind of data.

Another crucial aspect when dealing with a study in the wild relates to the fact that is hard to foresee which devices the citizens will use to participate. With respect to a closed environment study in a laboratory setting, this element creates uncertainly and can lead to additional problems and issues that are device specific. Usually in this kind of studies the participants are given a single specific device that has been extensively tested, while in our study this was not possible. i-Log tries to overcome this problems because has been designed to work on any Android device with some very limited exceptions.

The focus of the Modal Split use case within the QROWD project relates to understanding how people move around the city. Starting from this we defined the requirements in terms of the data to be collected, which mainly belongs to the inertial sensors. We finally decided to leverage on the *GPS*, *accelerometer* and *gyroscope* sensors. We added an additional virtual sensor that could help in detecting the *activity performed* by the user that is provided on the device as s Google service. This sensor returns a label among "running", "walking", "still", "on a bike" and "inVehicle" with an attached accuracy value, in percentage, from 1 to 100. The selection of only these few sensors with respect to all the ones available in i-Log perfectly matches the principle of data minimization required by GDPR, that is defined as *"Personal data shall be... (c) adequate, relevant and limited to what is necessary in relation to the purposes for which they are processed".*

The other element that has to be specified when using i-Log as data collection tool is the frequency at which the data are generated by the internal sensors. Similarly to the previous point, this is highly dependent on the use case but can also be capped by external conditions, i.e., limited storage size, limited internet connectivity, battery constraints, among others. For the Modal Split within the QROWD project we didn't have particular constraints and we decided then to go for the most efficient solution, that balances the amount of data collected and the recognition performances, being $20Hz$ for the inertial sensors [9]. The motivation for this relies in the Shannon–Nyquist theorem as reported by [10], that states that for a successful loss-less reconstruction of a particular signal, the data needs to be sampled with at least twice its highest frequency, being $10Hz$ for human movements such as walking, running, or cycling. Concerning instead the other sensors, namely the GPS and the activity performed, the frequency has been set to one value generated every minute or $1/60Hz$. The reason why this frequency is much lower with respect to the inertial sensors differs from one to the other. For the GPS the main limitation was the battery capacity of the devices, in fact, this sensor is the most energy demanding one of modern smartphones [11]. In order to don't affect the user experience by draining the battery of the device, we decided to sacrifice some location updates and obtained a full day battery life. On the other hand, for the activity performed, the limit was imposed by Google that to not allow to have higher updates.

Table 1: Sensors and frequency recorded by i-Log

Sensor	Accelerometer	Gyroscope	GPS	Activity
Frequency	$20Hz$	$20Hz$	$1/60Hz$	$1/60Hz$

Table 1 summarizes the sensors use for the Modal Split case study with the corresponding logging frequency.

The citizens were required to use the i-Log application on their mobile devices for a period of two weeks, every day for as many hours as possible in order to detect all their trips in the city. At any moment, the user could stop the data collection in compliance with GDPR and restart it whenever he feels to.

4.2 From raw sensors data to trips

In an average day, i-Log collects about 100Mb of raw data produced by the sensor installed on the devices of its users. i-Log sends daily such data to the database for the storage. At this stage, such data are still raw; thus difficulty interpretable. For some data streams, trip identification and modal classification can be quite easy, e.g., a series of subsequent points, detected over a restricted amount of time, having coordinates that perfectly overlap those of a railway, can be inferred as a train trip. Nevertheless in some other cases, such inference is uncertain, or even impossible. Data collected by i-Log might be inaccurate or incomplete due to the technical limitations of smartphones described in section 4.1, representing a challenge for the learning component. Another issue that needs to be taken in consideration since highly relevant to the modal split computation is the presence of multi-modal trips. Multi-modal trips are trips in which the citizen changed the transportation mode multiple time from the starting point or the trip to the destination one. We call *segmentation* to the action of splitting a multi-modal trip into more single-modal trips. Correct segmentation is challenging, as transport mode changes tend to happen in a short period of time, making difficult to identify the exact point in time and space of the change.

Several works have looked at the implementation of Machine Learning classifiers to infer, for each day of data, the trips that citizens took and what was the transport mean used. Such classifiers can be studied in isolation, or in the context of a general workflow where results of the classification are sent to citizens in order to validate them, and use the citizen's input to implement a reinforcement learning scheme. We follow the latter scheme, as described in our previous work [13].

As purely machine classifiers, we implemented Decision Trees and Random Forest on top of gyroscope and accelerometer data. One of the challenges faced is to generate enough training data on the particular topology and available transport means of the target city. Our answer to that challenge is to start training on publicly available data, like the UCI Human Activity Recognition dataset or the, and then, using a reinforcement pipeline, increase the accuracy of the model progressively, each time a travel survey is applied. During the first iterations, the accuracy is low, and we expect to have to ask many questions to citizens to confirm and update their trips. The classifier is retrained after each survey (2 weeks worth of data collection on 20 to 600 citizens), progressively increasing its accuracy.

Our approach makes very important the correct management of the interface with citizens, as they are the only ones that can provide the real answer of the trip. As such, we analysed the most common errors committed by the Machine Learning classifier, in order to provide an appropriate interface for each of them. Figure 8 shows the five possible outputs of the trip segmentation process: (i) *No errors*, the segmentation is correct and perfectly in line with the trip made by the citizen; (ii) *wrong transport change point*, the transport modes are detected correctly, but the change point is wrong; (iii) *wrong transport mode*, the multi-modal trip is correctly segmented, but one or more transportation modes inferred are wrong; (iv) Under segmentation, the multi-modal trip in segmented into less segment than the expected (two or more segments are

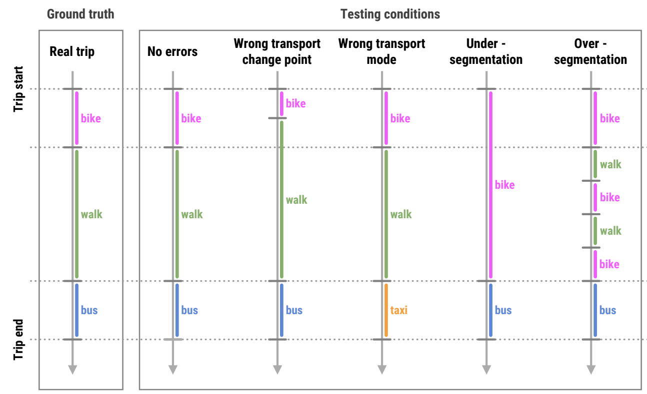

Figure 8: The segmentation process can lead to five possible outputs.

merged together); and (v) *over segmentation*, the multi-modal trip in segmented into more segment than the expected (some segment are wrongly divided instead on being together).

4.3 Trip confirmation

The capability of the classifier in generating an effective learning model, that allows identifying trips correctly, depends on the quality of the training set. In particular, an effecting tuning of machine learning classifiers requires a training set enriched with correct classifications. Initially, the classifier works with data collected from other cities, however, to enable continuous improvement, we implemented a feature that allows requesting for a trip classification directly to the citizen who generated that trip (usually in the previous 24 hours), via the i-Log app. The feature also allows municipalities to collect quality data for the modal split estimation from the first run.

i-Log allows to collect human feedback in terms of answers to specific questions administered through the application. These questions can be simple textual questions that require the user to select one among different multiple-choice answers, but can require the user to take more complex actions, such as localize herself, taking a picture or interact with maps. The questions are triggered by a *REST API* call to a backend server that leverages on Google Firebase [9] to deliver them to the devices. The principle behind the service is that Google opens a connection with the device when it is convenient to do so and in this window it delivers messages sent by multiple applications simultaneously. The messages for confirming modal split trips are composed by a JSON string that contains text and metadata. Similarly to the contributions for the challenges described in Section 3.4.1, the answers are temporarily stored on the device and synchronized with the backend server whenever a Wi-Fi connection is available. Figure 9 shows i-Log interface when requiring to a citizen to confirm a trip. On the left the view that asks about what the citizen did in the selected location. In the center, the citizen is asked to select which transportation mean she used for the highlighted trip. Finally, on the right, the

[9]https://firebase.google.com/

user is required to put a marker on the location where he changed his transportation mode.

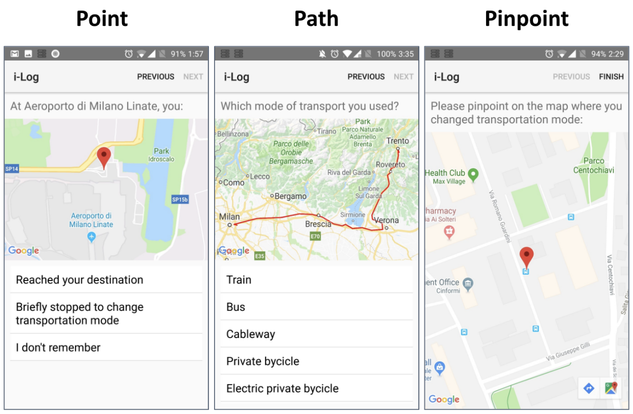

Figure 9: The interface of i-Log when requiring to a citizen to confirm a trip.

5 CONCLUSIONS

In this paper, we presented two human-machines hybrid workflows that make use of human computation strategies to engage with crowds (both citizen with a local knowledge of the territory and remote crowdworkers) to tackle two mobility related issues: the problem for public authorities of completing the mobility infrastructure maps and the estimation of the modal split. The solutions presented are part of a big picture in the context of the ongoing QROWD European Project. The studies discussed varies in several factors, such as the type of crowd, engagement required, and costs to sustain. Our ongoing research covers such aspects, aiming at developing a homogeneous integration of the proposed services in order to provide a platform for end users, who might need to use crowdsourcing services even without having specific technical knowledge. On one side, we used the i-Log application to engage directly with the citizens, and leverage on their data and knowledge to achieve the defined goals. On the other side, we leveraged traditional crowds.

Our preliminary results on the mobility infrastructure workflow [12] show that the crowdworkers can complement current datasets very well. However, this is a limitation for areas that are not currently covered by an on-field agent. Further research is required to identify areas where remote crowdworkers cannot reach, and combine with appropriate spatial crowdsourcing techniques to send field agents only to those locations.

With respect to the Modal Split workflow, our initial experiments show that our machine learning classifiers show similar accuracy than state of the art ones, however, better strategies to drive the reinforcement learning need to be developed, in order to boost the effect of making many surveys. Interface-wise, our approach was very effective for confirming true trips and fixing positional errors, but was not so effective to solve oversegmentation types of errors (especially when there are many segments). Further research is required to design an appropriate UI for this case.

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