A Collaborative Framework for Annotating Energy Datasets

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***Abstract*—Targeting human activities responsible for the energy consumption instead of focusing solely on single appliance feedback for achieving energy efficiency in residential homes would link human behaviors to the resulting energy consumption. To this end, learning when appliances are in an *active* or *idle* state and the related user activity is crucial. Until smart appliances become widespread and can communicate their internal state, identifying when the residents interact with the appliances has to be determined from the available information that can be recorded from these devices. Developing and validating learning models require ground truth in the form of annotations to indicate when an appliance is *active* or *idle*. Launching data collection campaigns to incorporate these missing ground truth data involves careful planning before the roll-out of the experiment. Prohibitive costs for the hardware and time investment to monitor the deployed equipment are necessary for quality data. As such, publicly released datasets containing appliance-level data offer a basis for most researchers. This paper addresses these challenges by providing a collaborative web-based framework to retrofit labeling on existing datasets. The platform is publicly available, applies the wisdom of the crowd in the realm of energy research and leverages gamification techniques to encourage users' active contribution. The access to the platform and furthermore to the expert manually labeled dataset intends to enable future research and foster more collaboration in this area.**

***Index Terms*—Information systems applications; Data mining; Collaborative computing, Computer-supported cooperative work; Energy disaggregation; Activity inference; Appliances states; Energy data analytics; Datasets; Ground truth acquisition**

I. INTRODUCTION

Achieving energy efficiency in households requires integrating the residents in the loop. At the moment, most utility company customers are only accustomed with the format of monthly bills as a feedback for their electricity usage. As a result, they are often over- or under-estimating the consumption patterns of their appliances and are not familiar with energy jargon [1, 2, 3]. Confronting them with concrete information, and in particular, providing real-time feedback was estimated to offer higher potential energy savings under the best conditions [3]. Additionally, a smart home agent can incorporate an ambient intelligent system that monitors the residential consumption in real-time and control appliances based on usage and occupancy patterns. Understanding human behaviors incurring energy consumption would allow us to determine when and which appliances are triggered together to perform those activities. This would enable us to give energy savings recommendations at the activity level and extend the range of measures to improve energy efficiency. A user would thereafter be able to optimize their energy consumption to their own individual needs, thus, making choices that cut the energy bill without sacrificing quality of life.

Learning users' activities requires determining when humans are interacting with appliances. While static thresholding has been used in prior work [4, 5], these methods are not agnostic of the appliance type and model. Therefore, any effort to produce a learning algorithm for automatic thresholding [6] requires ground truth data, i.e., an indication of when an appliance is turned on or off by the user, for validation. However, acquiring high quality data demands efforts for planning, deploying and monitoring the experiment, and incurs considerable costs [7]. While the infrastructure installation does not involve the active participation of the households' residents, the acquisition of ground truth data requires human efforts for the annotation of events. This task has to be carefully designed to be simple enough and should not induce user fatigue in order to guarantee the labeling quality [8, 9].

Real-world ground truth data are required for validating or inferring models in different fields that rely on machine learning. As the algorithms rely on supervised or semi-supervised learning techniques, the need for ground truth data has increased. Common but helpful tasks such as determining which email should be classified as spam benefit from sets of sample junk mails, but the fine tuning of the the classifier still requires the users' participation to reduce false positives and false negatives. In computer vision, object recognition relies on the segmentation of an image (similarly to performing it on the frames of a video) to indicate what objects are present, but also where they are located. Attempts at building large sets of human annotated images involve crowdsourcing the efforts and relying on gamification [10] or a collaborative framework [11]. CAPTCHAs [12], which are traditionally used for verifying that a user is human and not a robot before granting them access to a resource, are now diverted to extract street numbers for Google Street View. Research topics in computer science are not the only ones requiring ground truth data, as the study of the genome and the understanding of the function of each gene is also adopting the strategy of crowdsourcing the efforts in their community [13].

In the energy domain, efforts have been deployed to offer toolkits for simplifying the deployment of data collections [7] or the evaluation of NILM algorithms [14] on the most common publicly available datasets. The existing literature shows that in the case of the appliances, considerable progress on the understanding of the energy signature of devices has been made [15, 16, 17, 18]. Existing attempts at obtaining ground truth data for ON-OFF events depend on human supervision for the annotation of existing energy datasets obtained through an event detection algorithm [19]. More complex annotations such as acquiring human activities labels were achieved through a web platform [9]. However, there has not yet been any initiative to take advantage of the wisdom of the community on energy disaggregation to annotate existing datasets.

"Crowdsourcing systems coordinate large groups of people to solve problems that a single individual could not achieve at the same scale. Microtasking systems typically use highly-controlled workflows to manage paid, non-expert workers toward expert-level results. While these crowdsourcing approaches are effective for simple independent tasks, many real-world tasks such as the ones in design and engineering require deep domain knowledge that is difficult to decompose into independent microtasks that anyone can complete." [20, p. 1] Consequently, most crowdsourcing workflows and algorithms aim to structure non-expert contributions to produce expert-level performance.

In this paper, we propose to leverage the knowledge acquired through NILM research to annotate the Pecan Street dataset. This dataset was collected in the frame of an experiment involving a smart grid demonstration project in Texas and provides electricity, water, and natural gas and solar generation measurements [21]. The publicly available version of the dataset we use contains appliance-level data and thus, does not provide state information about the appliances, i.e., when they are *active* from when they are in standby mode or off. Thus, the task consists in indicating when an appliance is powered on and being actively used to serve a human activity and when it can be considered *idle*. Our approach brings expert crowdsourcing to the very specific domain of labeling and annotating energy events in public datasets. Unlike other domains where we can leverage the wisdom of the crowds, here the activities require expert knowledge from the community. Regardless, we make use of gamification techniques to promote expert user participation.

We attempt to provide an easy to use framework as a modulable plugin that can be used on existing publicly available datasets to provide crowdsourced annotated data to energy experts and made freely available to the community. We summarize the key contributions of this paper as follows:

- We describe the design of a web interface for the annotation of a power trace dataset (such as the Pecan Street dataset) and relying on an intuitive approach, from the users' perspective, with simple drawing tools;
- We describe the design of a fetching engine to keep track of single users' and the crowd's performance overall, providing a consistent annotation flow and ensuring data consistency and motivating users' contribution;
- We explain how our approach fosters interaction among researchers in the domain, leveraging the wisdom of experts, and thus contributing to the future research in this area by providing access to the annotated data.

The remainder of this paper is organized as follows. Section II presents related work. Section III introduces key components of our annotation framework. Section IV describes the motivational techniques we include in our design to engage users' participation. Section V discusses results obtained through the usage and evaluation of our platform by test users. Section VI explains how the data acquired through our system can be disseminated among the community. We conclude by discussing lessons learned and future work in Section VII.

II. Related Work

A. Home Energy Analytics

Launching an energy data collection in residential environments requires finding volunteers and efforts in planning. Efforts to maintain the hardware and solve failures or other anomalies that could be introduced by the faulty behavior of the residents are necessary to guarantee the quality of the data. Some issues can be alleviated with the usage of a framework like Piloteur [7], as it can serve as a best-practice basis for the deployment back-end. However, a real-life experiment involves monetary costs in terms of the measuring equipment, but also for the installation, as the complexity increases depending on the household's setup and the appliances and circuits that should be monitored. Efforts in terms of time and costs are thus often prohibitive and discourage the acquisition of new data.

The energy community has benefited from NILM research, as they have collected and shared disaggregated data. The datasets vary in the number of households that were included in the experiment roll-out, the type of appliances and circuits that were monitored, the duration of the data collection, the type of data that were collected (power, voltage, etc.) and their granularity. REDD [22], BLUED [23], Smart* [24], Pecan Street [21], iAWE [25] ECO [26] allow the community to benefit from the efforts of the groups and the organizations that initiated those data collections, but also provides lessons learned for prospective setups.

B. Other Domains

Data analytics techniques are applied to increasing amounts of collected data to extract knowledge from them and are assisting in the verification of models in diverse domains. Diverse applications require human input to improve the quality of a classification algorithm such as spam filtering or Internet search [10]. NELL, the autonomous learner system requires adjustments to its newly acquired categories by integrating some daily human interactions [27]. Crowdsourcing has also become popular for providing metadata for Twitter messages [28].

However, not only computer scientists, but also biologists are faced with large data amounts in their quest to understand gene functionality. There have been efforts to integrate annotations collaboratively in a structured way for the Zebrafish genome [13].

Computer vision is a field where the diversity of the concepts that should be captured by images and videos requires large collections of real-life examples to be collected. General labels can be obtained from content description in the HTML anchors for images [29]. While *CAPTCHAs* were at first introduced to differentiate robots from human users, by carefully embedding images in them, labels for text and image recognition can be obtained with varying degrees of accuracy [12]. However, precise segmentation of objects would require a different environment design and more focus on the task. Prior work in this domain has already considered crowdsourcing segmenting images and labeling areas of interest in images [30, 31, 32]. The integration of gamification into the labeling pipeline was already regarded by the computer vision community to reduce the tiredness incurred by the task [10].

III. Framework

We named our collaborative framework CAFED for Collaborative Annotation Framework for Energy Datasets[1]. A view of the framework is available in Figure 2. The system architecture can be seen in Figure 1. The technical implementation details can be accessed as additional material on our GitHub repository.[2] We discuss the key components in the following.

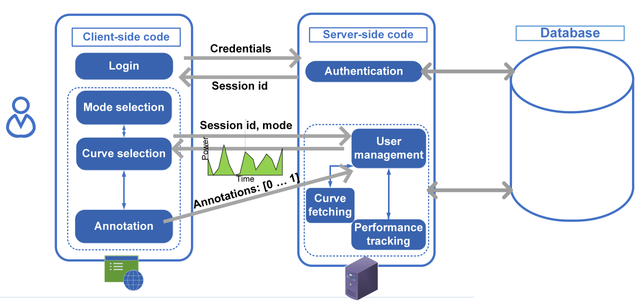


Fig. 1: CAFED architecture, based on a web server architecture with a database for handling 3 key components: security (authentication), curve dispatching and annotation.

A. Database Architecture

1) WikiEnergy Database: CAFED uses the Pecan Street dataset,[3], which was curated and hosted by WikiEnergy. The data were collected from January to May 2014 in 239 households and include 73 categories of appliances and circuits and provide 1-minute measurements. The original Pecan Street data are stored in a PostgreSQL database in a spreadsheet-like format. Each row of the table has the following attributes: the household id, a timestamp with time zone information, a real value that stores the total power consumption at the corresponding timestamp, and real numbers for all types of appliances and circuits that were monitored over the whole dataset. This means that for each row, a lot of columns are empty. We normalize the WikiEnergy database in order to optimize updates and inserts for our framework and provide a detailed Entity-Relationship Diagram on our GitHub.

B. Security

Since the framework consists of a web-platform, several measures have been taken to guarantee the users' confidentiality and privacy. Prospective users are encouraged to sign up for an account, where they can choose a username and share their full name and email address. The authentication is handled by phppass[4] and passwdqc,[5] which are based on recommended methods for salting and hashing the passwords. The user is provided with the option to change their password at their convenience and to create a profile with additional information such as their addresses and their affiliation (only university at the moment). The relevant data are stored in two separate tables in the database. We considered using location (derived from the address, country, affiliation or IP address of the users) to offer additional gamification features based on the location of the contributors as will be discussed in Section IV.

Additionally, typical measures for banning malicious IPs, session management and different attacks are implemented following the OWASP[6] guidelines.

C. Dispatcher

The dispatcher is handling the fetching of the curves to be annotated by the experts and guarantees a dynamic and targeted assignment of the missing labels. It relies on the use of a fetching table to keep track of how many annotators have been allotted a given power trace (pending annotations) and how many tasks were fulfilled to consolidate the result (committed annotations). The fetcher is called by a function that queries and updates the fetching table and returns the data to be annotated to the user. The data quality is enforced by the use of majority voting to decide the final value to be attributed to a given measurement in a power trace, the first objective to reach would be to obtain three annotations per curve. Once that this value is reached for all the readings, we expand the threshold to the next odd number.

The dispatcher implements two modes of operations for the curve attribution. The user has the option to randomly display curves by letting the dispatcher choose the household and the appliance type or circuit. The alternative allows the user to select the type of appliance for their assignment. Using this schema, the fetcher is keeping track of the available data that still need to be annotated for that specific selection and when a household is identified, it will try to maintain continuity by attempting to attribute power curves from the same household

[1]https://cafed.inf.ethz.ch
[2]http://github.com/caoh/CAFED
[3]http://www.pecanstreet.org/
[4]http://www.openwall.com/phpass/
[5]http://www.openwall.com/passwdqc/
[6]http://www.owasp.org/

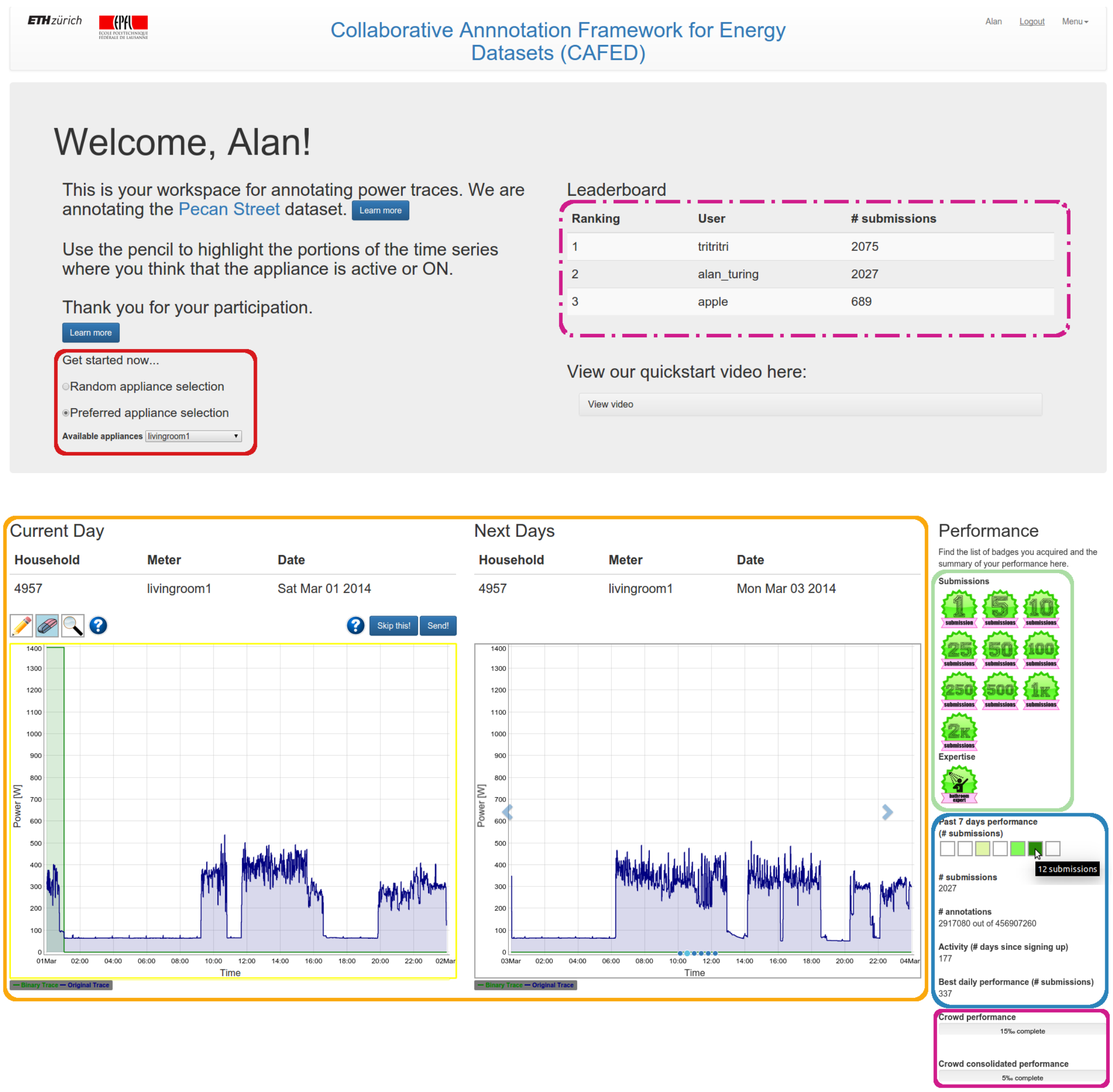


Fig. 2: Annotation framework. We highlight in red the curve selection and in orange the annotation workbench. The personal performance component is highlighted in blue, while the competitive components are in purple. The badge section shown in green highlights the badges acquired by the user.

day, after day by keeping track of previously annotated data by the same user.

D. Annotation

The objects to be annotated consist of time series over the span of a day. This allows the user to correlate potential events arising during a day to variations in a power trace and to decide which changes can be attributed to a device or circuit being powered on. Similarly to the problem of segmenting objects in an image or a video [11], we require the annotator to highlight portions of a power trace to indicate the occurrence of an event, in our case, when the appliance is *active*. We integrate a toolbox with drawing features to enable the annotation of portions of the curves as can be seen in Figure 2. We binarize users' inputs by transforming the highlighted areas into ones, while setting the rest to zeros.

IV. User Engagement and Motivation

Crowdsourcing has largely focused on tasks any individual can complete: many crowdsourcing platforms are built to accomplish tasks that require little training (e.g., Amazon Mechanical Turk) and recruit amateurs (e.g. FoldIt). Also, at the moment, those platforms are not suitable for more complex tasks that require an interactive interaction with the data to be annotated, in our case, time series. They are instead designed to provide content description through categorical or survey type of annotations (obtained through text fields, tick boxes or lists). Consequently, most crowdsourcing workflows and algorithms aim to structure non-expert contributions to produce expert-level performance. In the energy domain the annotation process requires experts that are capable of understanding and labeling the power events.

Using arbitrary set thresholds [33] does not perform satisfactorily in cases where the baseline consumption is above and will not scale with the diversity of appliances and baseline consumption profiles. In the case of circuit-level at the room level, the energy used by consumer electronics in standby mode adds up and will vary from one household to the other, making the definition of a threshold difficult to scale on a large set of households. Additionally, appliances in standby-mode should not be considered actively in use, so the notion of baseline also applies to them. Given the diversity of appliances and intra-categorical variances due to brand, model and production year differences, deriving this information without expert knowledge about the expected power signature of electrical devices and notions about the mechanical functioning of the appliances would induce the amateur annotators to label the time series incorrectly. As can be seen in Figure 3, in the case of *dishwasher1*, the expert recommended highlighting the activity in one block because of his knowledge of subsequent cycles through a washing program (instead of producing segmented annotations as the power dropped to the baseline). Then in the case of *livingroom1*, not only is the baseline to be decided upon, but small peaks before 06:00 could be interpreted as an activity diverging from the baseline, while side information such as when these arise and their frequency would indicate otherwise.

Our design sets expert annotators at the core of the system, as their contribution is essential to the building of the manually labeled ground truth data. We discuss ways to facilitate users' interaction with our system and how to acquire their loyalty. We consider different means of motivating the domain experts to participate. We expect two profiles of users, namely (i) experts whose research interests can benefit from the dataset, (ii) experts that are altruistic and wish to contribute to the community. In the case of the altruistic contributor, we integrate both intrinsic and external motivation elements [34] in the form of gamification techniques to alleviate the repeatedness of the annotation task. Obtaining the dataset is also considered as a motivational tool as will be discussed in more details in Section VI. We describe below the elements that are implemented in the framework.

A. Annotation Task Simplification

With such repetitive task as the annotation of data, users are required to familiarize themselves with the platform and to be able to interact with it efficiently. The perception of the easiness or difficulty of handling the tool will influence the contributors' willingness and thus motivation to use it [34].

1) Curve Selection: We decided to embed two modes for curve selection in CAFED, namely the random and appliance-specific modes as can be seen in the red area in Figure 2. Both modes can be selected by choosing the appropriate option as the user logs into the platform. The random mode allows the dispatcher to select the curves randomly as described in Section III. If the user is not comfortable with the curve they were assigned to, we embed a skip button to query for another appliance. The appliance specific mode allows the user to choose the appliance they are the most familiar with. This might speed up the annotation progress, as the user can put their expert knowledge into practice, while the random mode allows for more diversity and surprise. The skip button allows to navigate between households. To minimize interactions with buttons and other input interfaces and preserve the annotation flow dynamics, after the user has submitted their annotations, a new curve is automatically selected by the dispatcher based on the user's preference and displayed again in their workbench.

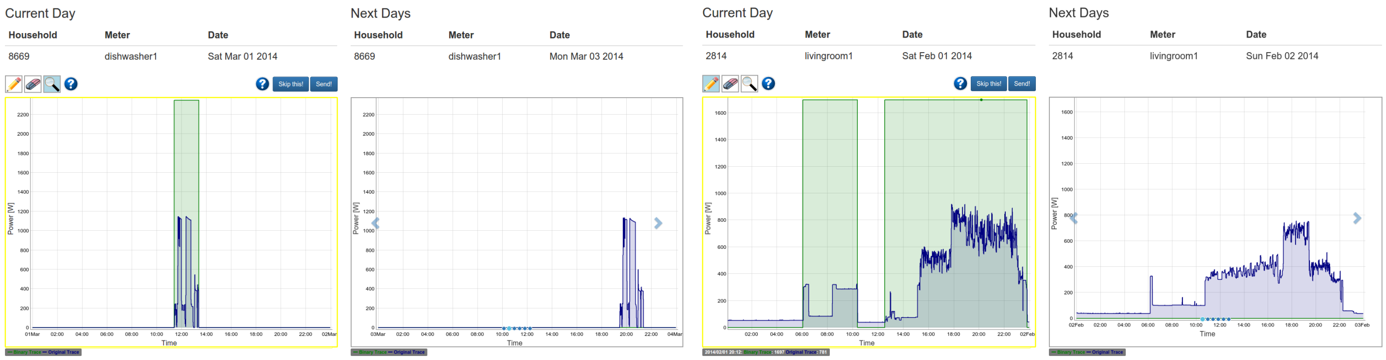
2) Curve Annotation: We consider that the most natural way of indicating which area of a curve represents a period when an appliance is *active* would be to draw or highlight it with a marker (similarly of locating objects in a image). The user is thus provided with a toolbox consisting of a pencil, an eraser and a loop (and their respective icons replace the cursor in the panel that contains the curve to be annotated). This enables an interaction similar to using a sheet of paper and a pen in the physical world for the annotations as can be seen in Figure 3. When selecting the drawing mode, regardless of the height of the cursor (which takes the appearance of the icon representing the feature currently on), clicking and dragging it to the end of the desired area will act as a highlighting feature. We also integrate the option to erase the annotation and to zoom in to focus on curve portions.

We also pay attention to the layout of the information as to facilitate the decision process for the areas to be annotated. We combine a view where the user can compare the original curve in blue to its binarized version in green as can be seen in the workbench in Figures 2 in orange and in 3. We display information relating to the curve such as the household's ID, the type of appliance or circuit that is represented and the day on which the data were recorded. In order to have side cues on how the data should be annotated, we add the next 6 days in the right panel for the same appliance and household and always normalize the graph's y-axis to the appliance' maximum power reading over all data available for the considered household to avoid scaling confusion. We preserve the chronology of the curves by displaying the current curve in the left panel, while the next days are shown on the right side. These measures are embedded to guarantee consistence in the annotation process and to provide side information to the annotator.

B. Gamification

In our setup, we assume that users are content contributors. In particular, we intend for the annotations to be provided through crowdsourcing by domain experts and thus, be trustworthy data, as they have the necessary knowledge to provide the appropriate labeling of the data. Since annotating energy datasets is an activity that would hardly be decomposed into independent microtasks that anyone can complete, we differentiate ourselves from the usage of other crowdsourcing platforms. In addition, using services like Mechanical Turk would imply having to monetize the effort and evaluate the quality of the workers' contribution or even to select the appropriate workers [35].

Regardless, in an effort to motivate users' participation, we integrate some gamification concepts to foster user engage-



(a) Single appliance: dishwasher1

(b) Circuit: livingroom1 with noticeable baseline consumption

Fig. 3: Annotation workbench in the case of a single appliance and circuit-level data

ment [36, 37]. We focus here on two intertwined techniques, namely feedback through performance tracking [34] and the usage of badges. From a socio-psychological standpoint, badges offer a set of attributes, which combine educational and social influences on users' motivation [38].

1) Performance Tracking: Performance tracking can be twofold: allowing the user to keep track of their own progress or to position their contribution in comparison with the rest of the participants. Live feedback on the user's performance assesses the user's past contribution and contributes to their motivation [34]. We implement the latter in the performance panel, which is located at the left of the workbench as not to distract the user too much from their task, but still being close to the eye if the user wants to peek at the information as can be seen in blue in Figure 2. The user's personal performance combines statistics about the number of data points and the equivalent number of curves were submitted, the number of days since signing up or the user's best daily performance. We also display the user's past 7-day performance in the form of 7 squares that can take varying shades of green depending on the number of submission for each day (white for 0, a pastel green for 1-2, an apple green for 3-9 and a dark green for over 10). By placing the cursor above a square, the user can view the exact number of submissions for a specific day. As will be explained in Section VI, the user's contribution is rewarded by the release of the data. The historical feature can assist the user in the scheduling of their contribution and to motivate them to provide submissions frequently, until the data are unlocked.

We introduce competition by showcasing the user's performance against the other group members with a leader board as can be seen in pink dotted lines in Figure 2. The information appears in the welcoming section as to be the first information to be displayed upon logging in. This not only should motivate the user to improve their rate of contribution as they compare themselves to others, but also provides recognition as a reward, as all annotators are faced with this information [34]. As mentioned in the Section III we could add more leader boards based on categories to value the users' performance in subgroups where they would rank higher (based on their affiliation, on the continent or the country they are located in). We add information about the collaborative effort of the community in the form of progress bars in the performance panel on the right side of the workbench as can be seen in pink solid lines in Figure 2. This information consists of the progress in labeling the time series (distinctively for each time series and in a consolidated manner, where the minimum number of annotators has been reached for each time series).

2) Badges: As platforms such as Stack Overflow[7] provide free support for users from varying backgrounds to ask question and contribute answers, badges were introduced to reward contribution. This, as a consequence, also provides an appreciation of the contributors' knowledge by their peers and based on their pedigree. Carefully placing badges can steer the user's behavior towards targets set by the platform designer and this effect increases as they approach the boundary to gain them [39]. Content generation of geo-tagging data was also boosted on Foursquare by the usage and constant addition of new badges to be acquired by users that were checking in at places they visited. Using badges not only enforces user loyalty or boosts and rewards performance, but also, some pedagogical feedback can be given to the user [37].

Our badges are awarded for different types of behaviors and can be grouped in different categories as can be seen in the green area in Figure 2. In the following, we explain the goals that should be achieved with the diverse categories of badges we intended to include. Some side effects of awarding some badges can be linked to performance tracking as well. We use an alert box in green to attract the user's attention to the acquisition of the latest badge. As we cannot expect the user to read the information page that also provides an overview on how badges can be obtained, the box also contains an explanation as of why they obtained the badge. The badges are placed by categories as to facilitate the reading of the information and keeping track of the badges acquired. By using this design we acknowledge the user's performance in real-time and, by incorporating an additional way of signaling that a badge was acquired, we avoid that the information gets lost (pop ups can be distracting and as a usual habit, can be

[7]http://stackoverflow.com/

closed to prevent inconvenient alert windows, which are usually associated with advertisement).

a) Submissions Badges: We differentiate badges that are permanently awarded for a particular milestone and ephemeral badges, for which a regular performance has to be provided in order to maintain them in the user's badge collection. While we provide an information page that not only describes the purpose of the framework and the how to acquire badges, we include some badges that are designed to positively enforce the user's interaction with the annotation system by acknowledging their contribution. For example, we add the *submission* badges, which are received when a given number of submissions is achieved. The contribution is already rewarded with one submission and validates the user's first interaction with the system as being correct and successful. The *submission* category is at the moment the only one intended to use leveling for the same type of badges, as to reinforce a given purpose, which is in our case to attract more submissions. They are relatively easily achieved as to motivate the user to contribute even on a small scale already. The target number of submissions can of course be extended to encourage the user to contribute more.

b) Expertise Badges: We also encourage exploration by having *expert* badges that are awarded as a larger range of types of appliances are annotated. Using both the random and the appliance selection modes, the succession of curves that are assigned to them or the different appliances / circuits that are picked by affinity can lead the user to collect an expertise badge by chance. Although we could have used levels such as with the *submission* badges, we first decide to reward curiosity, which means that once that all appliances in a group have been annotated once, the badge is delivered to the user. We could extend it to other *expertise* badges to foster relentlessness in a given field or for one specific appliance or circuit.

We establish natural groupings of appliances / circuits and create the corresponding badges. For example, an expert badge is awarded once that all appliances that could be found in a group have all been submitted at least once. Concretely, the bathroom expert badge is awarded for the appliances linked to the bathroom environment, while the chef badge rewards curiosity in the kitchen area. The climate expert badge can be obtained by annotating all corresponding climate regulation appliances. The explorer badge is awarded for thinking out of the box, for submitting annotations for appliances that are not so widespread across the dataset such as a wine fridge or appliances with the `unknown` label. The *light* expert badge can be gained by labeling all lights, while the outdoor badge relates to appliances that can be found outside of the household. The home owner badge is awarded once that all appliances in a household have been annotated at least once and thus, this depends on the dispatcher's selection.

c) Ephemeral Badges: The previously presented badges were forever awarded badges. To influence the user's loyalty and thus frequent contribution, we add ephemeral badges. Daily attributed badges reward current performances and consistency badges and require the user to contribute more frequently over time. Top contributor badges are awarded for the user's ranking over the previous day and require that they top the other participants on the current day to retain the badge. The endurance badge is intended as a motivational tool that is triggered once that the user has submitted 10 submissions over the course of the current day. We also add the frequent flyer badge, which can be obtained once that the user has contributed at least once per day on five occasions over the course of a week. This badge can be kept as long as the previously explained ruled in respected in the span of 7 days. Finally, the champion badge rewards a contributor that have annotated all curves in the dataset, to target over-achievers.

TABLE I: Summary of the collected manual labels

Result	Value
Total # annotated curves	4856
# curves annotated by 3 annotators	469
# curves annotated by 2 annotators	572
# curves annotated by 1 annotators	2548
% curves annotated by 3 annotators	0.5%
# users	9
# badges distributed	174

We could of course add more rules, more badges and probably a continuous renewal process to integrate more badges in a similar way to Foursquare to retain users.

V. Results

To the best of our knowledge, CAFED is the first system that provides a dynamic attribution of time series to be annotated by expert users, while consolidating the already annotated traces. Also, through the platform the results are stored and compiled in a ready to be deployed format. Most users have easily associated the annotation process with the highlighter and paper equivalent. Users have reported to require a few seconds to a few minutes (in case of very segmented portions of curves to be annotated accurately) to commit their annotations. The first badge is awarded after one single submission and the users have recognized that it was perceived as a confirmation that they had correctly interacted with the platform. Most users have taken great care with zooming in and out to accurately indicate the start and the end of the task. When the users thought that they needed to justify their annotation, they provided us with an explanation for their reasoning. From their feedback we have realized that more features are needed to allow a comparison with other users' annotations. Some are made available in the appendix.

The top three users provided the majority of the annotations with 600 annotations provided in the span of 2 weeks and devoting an average of 90 minutes per day for doing so. We provide an overview of the data collected so far in Table I.

VI. Giving Back to the Community

Substantial progress has been enabled through the public release of datasets. Through this framework, we intend to give back to the community by providing access to annotated data. We follow in the footsteps of platforms such as WikiEnergy[8]

[8]Now known as Pecan Street Dataport

or NILMTK[9] to provide a unified access to an online platform to facilitate the creation of manually labeled ground truth data and their dissemination in the community.

A. Combining the Results

Although we are targeting domain expert users, we envision that their annotation will not always agree. However, by relying on the wisdom of the crowd, we decided to consider majority voting to consolidate the annotations of the data points. Concretely, each curve is assigned to an odd number of annotators and the final outcome relies on the combination of the majority's decision for each measurement. We start by requiring 3 as a minimum to be reached, which means that at least two similar annotations for a given data point are necessary and will yield its value eventually. As to increase the credibility and quality of data, as the number of converging decisions increases to reach a consensus, we decided not to stop once that the threshold of 3 annotators per curve has been reached, but to continue to the next odd number and so on.

B. Downloading the Data

Our goal is to share these ground truth data with the community. However, this can only be possible once that there are data to be shared. We decided to release the dataset progressively to contributors, as they reach certain levels of contributions. This can be seen as another gamification technique. In this perspective, we opt to reward frequent and numerous submissions. This can be represented by the combination of two badges, namely the *endurance* and the *frequent flyer* badge, in the form of the *download* badge. This means that all the data available can be downloaded as soon as both badges are available in the user's badge collection. The user could of course only provide 1 submission per day on 4 days over a week and provide 10 submissions on the 5$^{\text{th}}$ day, but this still means they should have contributed 14 submissions. They will need to have obtained the *download* badge again to maintain their access to the current set of annotated data. The absolute figures in terms of available data to be downloaded are subject to change as the data provided by the community are increasing.

VII. Conclusions

A. Lessons Learned

The curve fetching engine requires an optimized access to the time series. This requires a clear entity-relationship model and optimized indexing and the creation of assisting tables (as table joins can be inefficient if only partial information is required) for enabling the data query. Depending on the granularity of the measurements, extensive care has to be taken to estimate the number of records to be stored in the database. Inadequate data types will also quickly overflow.

Having separate but replicated development and production environment allowed us to experiment with framework changes, without impacting the user's experience too much. Having experienced data issues, backups allowed us to revert to previous versions and having additional data consistency constraints avoided any data loss.

We launched a small user study for determining where our design was flawed. At the moment, we have tested our platform with 9 users who have provided over 4500 annotated curves. We have taken their comments into account in the design and the improvement of the platform. We realized that some features that seemed obvious and although documented in the Help section were not correctly identified or used by the users. This is why we had to incorporate a help video and help markers in the work bench to direct the users' attention to the embedded functionalities. Also, a detail that can greatly impact the quality of the annotation consists in the y-axis scaling before displaying the curves to the user. The dynamic scaling of the y-axis to the current curve data would produce inconsistency: lower power measurements (from the noise or the baseline) that would be unnoticed in the presence of active measurements would become visible for a day without the residents' activity and could be annotated. So, we proceeded to the scaling to the max value for all curves for the same household and appliance. After this change, users communicated that they did not necessarily notice the y-axis scale and were mostly looking at the shape of the curve and using the y-axis for confirmation.

B. Future Work

We have presented a modulable plugin that is accessible to the community via a web platform and combines design features to facilitate the annotation process and to engage the user. We follow in the footsteps of initiatives such as WikiEnergy or NILMTK. We do not exclude a merging of all tools under the same platform to regroup the efforts to provide access to data and tools to the community.

To improve the experience with the tool, we intend to add the possibility to search for annotation examples from other users. Similarly to Stack Overflow and as explained in [37] and in [38], we intend to show the status of different contributors by allowing them to interact with each other. This can be enabled by allowing a user to search for similar contents annotated by others and by displaying the user's badges status with their username. In the case where the plugin were to be merged with another platform like WikiEnergy, which allows additional interactions between users, such as posting questions on a forum, we could display a summary of acquired badges associated with the username of the poster. Also, we do not need to restrict the labeling to binary decisions solely, but could easily adapt the platform to incorporate multi-label problems by extending the toolbox at the disposal of the users to annotate activities that took place during the day for example.

In order to maintain the quality of the annotations and to prevent unintentional mistakes, we will add an amend option, that allows the user to correct previously submitted data. Also, we could envision pre-selecting *actives* sections and presenting the result to the user and only require for them to validate or correct the pre-computed result, similarly to the example developed by [11, 19]. Also, since we have as well annotated

[9] http://nilmtk.github.io/

an extensive amount of curves, they can be used as trusted data to verify and validate new users' contributions and discard malicious contributors.

We developed a modulable plugin that can be easily adapted to fit other datasets. By unifying the access to other datasets, we would also prevent ad-hoc solutions, where each researcher would have to build their own system and we show that the labels can be extended to encompass more events that determine when an appliance is *active* or *idle*.

We plan to use these data to evaluate the automatic thresholding algorithm presented in [6].

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Appendix

The users provided us with feedback that we included in the design of the framework. The comments and our responses are listed below.

1) What is the fastest way to get familiar with the platform?
   - We put a quickstart video online (you can see it from the start page and within the annotation page).
2) I've used the zooming tool but cannot zoom out. How do I proceed?
   - We've now added tooltips (move your mouse over those tools to get some hints) and added clearly distinguishable question mark icons with some more hints.
3) For each household, how do I make sure that the bursts and peeks I see for a specific (appliance/household) pair are not singular events?
   - First, we scaled the graphs to the maximum value for each appliance/household pair, to get an overview of the appliance's usage over the whole span of the data collected for this pair.
   - We provide additional side information (the next day following the current day to be annotated).
4) I believe that one additional day is not enough to get a feeling of whether an event happens by chance or whether there is a trend.
   - We now provide 7 consecutive days in total (the current day to annotate and the 6 next days).
5) I've made a mistake, how do I amend my annotations?
   - We are planning on releasing a correction tool to review past annotations. At the moment, please email the admin.
6) I do not like to use the mouse too much. What can be done to speed up the selection of the tools?
   - We now have added key strokes recognition. Press "s" for selecting the pencil, "d" for the eraser and "f" for zooming.
7) When can I download the data?
   - As soon as you've unlocked the download badge (meaning you have obtained both the frequent flyer and the endurance badges on the current day).