Estimation of Customer Activity Patterns in Open Malls by Means of Combining Localization and Process Mining Techniques

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Abstract. In this work we present a method to estimate the activity patterns made by shoppers in open malls based on localization information and process mining techniques. We present our smart phone application for logging information from sensors and a process mining system to discover what kind of activity pattern is made by the shoppers based in the key information of the localization which combine data mining, parallelization and monitoring techniques. Our system has been tested in a challenging scenario such as open mall (mixed classical mall and isolated shops in the street) where location is obtained by means of Global Positioning System (GPS) and a WiFi localization system that is helped by a parallel computing method to speed up the whole process. Activity patterns made by shoppers are obtained by process mining techniques which are applied to the data. The process models obtained provide hints that may help mall's managers to take specific actions considering the activity patterns that customers usually perform while in the mall.

1 Introduction

SOcial Workflows (SOW) coordinate the activities carried out by a group of users [6] who either individually or in cooperation try to achieve a certain objective. The SOW are unstructured flows in which a large number of users who carry out activities of a very diverse nature that they spread over time and typically consume few computing resources. An example of processes that are modelled through these types of workflows (WF) are the marketing campaigns that have as an objective to motivate potential customers in the consumption of a certain

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product or service. However, from a technological point of view, the characteristics of the SOW are: (i) they model unstructured processes where users have multiple options and/or paths, and where they can even carry out additional activities to those initially planned in the WF; (ii) a large number of users; and (iii) depending on the skill or motivation of each user, a same activity can be performed immediately or have a temporary duration much higher (in the order of hours or even days).

These characteristics add a series of challenges when managing and monitoring the execution of SOW. On the one hand, the management of this type of WF requires the handling of a large number of simultaneous executions whose duration extends over time. On the other hand, the analysis of the execution of the WF requires the use of process mining techniques [1] to obtain the real WF followed by the users and, in this way, understanding what really happens in the execution of the process, thereby allowing the improvement of the process and its (dynamic) adaptation to the needs of users. However, for unstructured processes with a huge number of executions, the results of the current process discovery algorithms are WFs that have a structure in spaghetti and therefore very difficult, if not impossible, to interpret. Therefore, it is necessary to develop techniques to extract valuable information about the discovered WF. This is the first axis around which pivots the project Business (Artificial) Intelligence for Social Workflows (BAI4SOW).

On the other hand, the BAI4SOW project adds another dimension to the SOW: the activities to be carried out by users take place in geographic locations (such as an open shopping center, an area of tourist interest, an area where some activity is carried out or, in general, any area of a city) and they are also geolocated activities that users carry out through mobile devices (such as activities of a marketing campaign). Therefore, it is necessary to capture the events related to the execution of this type of activities and, for this, it is required the development of localization techniques and detection of the behavior of users in a given geographic area. This is the second axis of the project BAI4SOW.

In this article, we present the results obtained in BAI4SOW project whose objective is in the development of process mining algorithms for SOW analysis that contain geolocated activities. In addition, given the high number of users who can potentially participate in this type of flow is necessary run the algorithms in grid computing, cluster and cloud infrastructures, minimizing the cost that this computation could have in business clouds like Amazon and Google. This is the third axis of the BAI4SOW project.

The paper is organized as follows, firstly BAI4SOW project is introduced, then localization process with parallel computing is presented, third, test-bed and activity patterns estimation results are discussed.

2 BAI4SOW Global Vision

The main objective of BAI4SOW is the development of intelligent techniques for automatic extraction and user behavior analysis in processes modeled through social WFs. In particular, the target processes are those involving users moving around an exterior area and carrying out the activities of the social WF through their mobile devices. To achieve this objective, a conceptual framework has been proposed composed by the following components (Fig. 1):

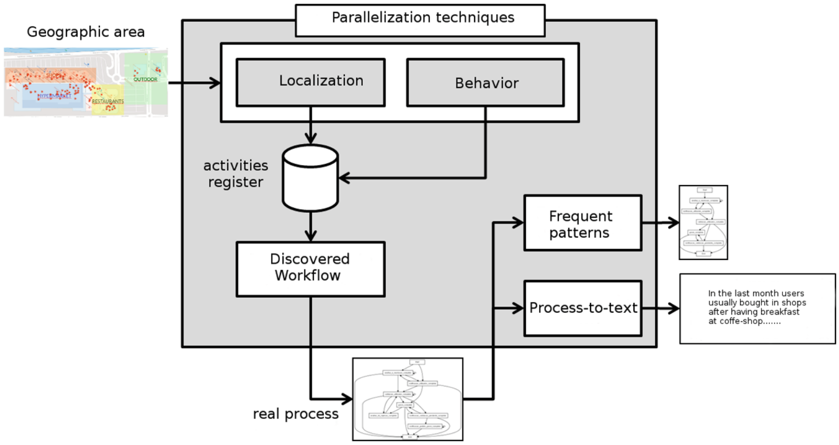

Fig. 1. Conceptual framework of BAI4SOW project.

- *Localization and behavior detection algorithms.* To analyze social WFs is necessary to record the events generated by the activities that each user carries out. For each instance of the process—an execution of the process from start to end—, a trace composed by these events is generated. In those processes involving users moving around a geographic area, this activities' model when a user arrives a certain point (to, for instance, make a purchase or take a photo), sits and moves inside an establishment, etc. Therefore, it is mandatory to *locate* the users in the geographic area where they are moving, as well as to detect users' behavior of interest once they are in a given location. To record the execution of these activities, a set of algorithms have been developed using the information given by the users' mobile devices such as the GPS and Wi-Fi signals sensors.
- *Process Mining Algorithms.* This set of algorithms allow to automatically discover the WF that has been actually executed by the users and, also, to extract relevant information about the process such as: *i) frequent patterns* of activities, which indicate patterns of frequent user behavior; *ii)* the *hierarchical organization* of unstructured and spaghetti WFs, which ease the visualization of the process reducing its complexity at different levels of abstraction; and *iii)* the *linguistic description* of these WFs, which automatically describes in natural language its most relevant characteristics, providing complementary information to the obtained by the users through the visualization of the WFs.

– *Parallelization techniques*. These techniques are used to design a technological infrastructure based on the integration of *grid* and *cloud* resources that support the efficient and large-scale processing of the algorithms developed under the project. This infrastructure integrates cost models to ease the decision of what computation and storage resources are more appropriate in each moment for the execution of the algorithms, considering the possibility of using resources from different infrastructures and suppliers.

It is important to note that this conceptual framework is applicable to SOW containing activities related to the location and behavior of the users taking part in them. However, process mining algorithms and parallelization techniques are directly applicable to any workflow in general, and particularly to unstructured processes with many users taking part in them. The following sections describe each of the components of this conceptual framework.

3 Localization System

As explained in the introduction, knowing the costumer's location is key to obtain heat maps representing the consumer movements and thus, to help mall managers to offer better marketing campaigns or change the shops layout.

In this paper, the method proposed to estimate users' smartphone location is based on the measurement of WiFi signals. WiFi-based localisation was selected because it is a no-installation, no-cost solution: There are WiFi access points (APs) in almost every shop, almost every smartphone has a WiFi interface and there is no need to be connected to WiFi networks to measure WiFi signal, so it is free of charge even for private networks.

Among all existing methods, fingerprint-based WiFi localisation is selected. This kind of methods rely on a two-stage approach: First, during the training stage, the environment is divided in cells and WiFi measurements are collected in each one of them. These measurements are then used to build the localisation system. Then, during the localisation stage, new measurements collected at unknown positions are compared with the stored ones to find the location where they were collected inside the environment.

The proposed method [7] follows this two-stage procedure and, besides, it implements a method to increase the localisation resolution without the need of increasing the number of cells to site-survey. This way, a Support Vector Regresion (SVR) algorithm is used to extrapolate virtual WiFi measurements at positions were no real samples were collected using the real collected information. Figure 2 shows the general architecture of the system.

As it can be seen, during the training stage, real measurements are used to create continuous WiFi surfaces from the collected discrete data using SVR. Using this method, one surface will be created for each existing WiFi AP. The trained WiFi localisation system will be composed of all these surfaces.

Then, during the localisation stage, a new sample collected by each costumer will be searched in these surfaces. This way, the coordinates where difference

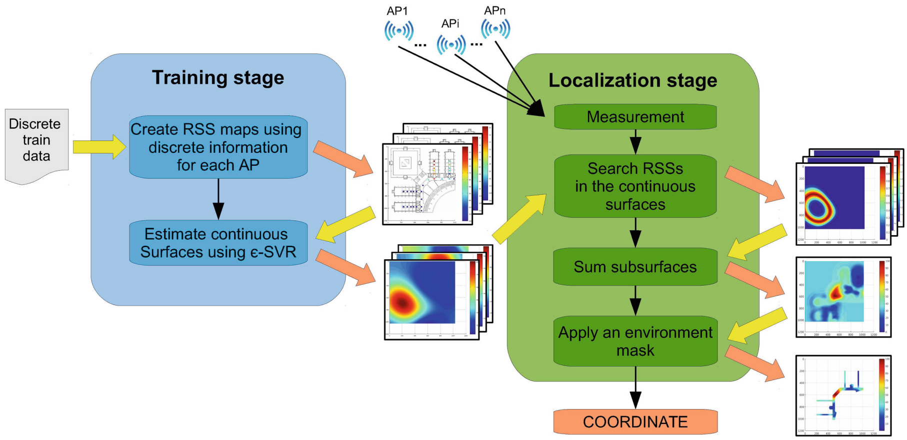

Fig. 2. General architecture of the system [7].

between the Received Signal Strength (RSS) from an AP and the stored RSS for that coordinate is low will be marked with higher scores than the coordinates with greater differences. Finally, the scores for each coordinate will be summed up, to obtain a resulting surface where the coordinate with the highest score is the most likely to be the location of the costumer.

In [7] the method was evaluated for determining the optimal size of cells when it is applied in a medium-size indoor scenario (around 2.500 m^2). The results proved that 15 cm side cells are an efficient option. In this paper, we are interested in evaluating the scalability of the method, from a performance point of view, and its applicability to bigger scenarios. For this reason, 1 cm side cells have been defined in order to increase significantly the number of cells to be processed for the same surface (25 million of cells in the scenario of 2.500 m^2). Besides, all the detected APs (a total of 105) and, as consequence, the 105 surfaces have been used to perform the localization. Two different trajectories were used to test the localisation system, obtaining mean localisation errors around 1,5 m. With this configuration, the execution times are 44.4 h to compute all the surfaces during the training stage and 325 s to determine the current location of a customer. The experiments were conducted using a server with 8 Intel i7-4790K CPUs at 4.00 GHz, a local SSD disk and 32 GB of RAM. Obviously, these performance results show the necessity of accelerating the training and location algorithms in order to be used in real scenarios.

As part of the work, a new parallel version of the algorithms has been programmed. It is based on the master-worker software architecture [3] and has been implemented to be easily executed in cloud-based enviroments. The solution has been deployed in the *Amazon EC2 infrastructure* (specifically, a pool of six *r4.8xlarge* computing instances has been hired to deploy the system programmed) being 16 min and 6.38 s the execution times of the training and location stages, respectively. The speed-up obtained in the calculation of surfaces and the location of customers is proportional to the number of cores available in the hired instances. Besides, the master-worker solution has been programmed as two RESTful services in order to facilitate the integration of the fingerprint-based location method in the BAI4SOW technological infrastructure.

4 Test-Bed and Results

4.1 Smartphone Application Development

In order to build the datasets and to set the ground truth, we have developed a smartphone application (see Fig. 3). This application is used in two ways: firstly the *training dataset* is collected by mean of saving several *paths* at static places, a path consists of frames at key points, and frames are formed by sensors' data and activities at zones and specific places introduced by an expert user; secondly *test dataset* is collected by mean of saving several paths with the user in movement. The activity, zone and place information introduced by the user for the *test dataset* will be used as ground truth in the validation stage.

The application is composed by a main activity and a service. The main activity is an interface to manage the application. The interface has an orange area with the buttons *START* and *STOP* to set the beginning and end of our path, and the name of the file that stores the data logging, as it is shown in the Fig. 3. In the green zone the actual user's selected activity, zone and place information is shown to store it by mean of pushing *SAVE* button. This tuple (activity-zone-place) is selected by pushing the buttons of the three white&blue columns. Finally, in the bottom part of the window, the Google API's recognized activity [5] is shown in order to compare it with our system.

Regarding service, it makes a log of all sensors' data. The advantage of this service is that runs in background, in such way, this allows the use of other applications without losing sensors' data. All the sensor's frames will be synchronized by mean of using the timestamp information.

When application is opened, the steps to follow are the next:

- First it is needed to write the name of the output file and then push the button *START* for initializing the service in background.
- We need to know our real activity for real comparison with Google's Activity Recognition API, which allows detecting users' activity using low power signals. Therefore, in the buttons of the three columns corresponding to place, zone and activity, we must select an option from each column and save the tuple. We will repeat this step every time we change activity.
- The last step is when *STOP* button is pushed, launching data saving in a compressed file.

Fig. 3. Screenshot of the smartphone application developed within the project

4.2 Test-Bed Description

The shopping mall *"C.C. La Dehesa"* is located in Alcalá de Henares (Madrid), this mall has 36.000 m^2 of indoor shopping composed by three big zones: 65 *shops* (orange area), one big *hypermarket* (blue area) and 7 *restaurants* (yellow area). In the shops zone, the ceiling is made by glass, permitting to obtain localization by GPS while in the rest only WiFi localization is available. In the outdoor area, fast food restaurants and shops are located. In this area GPS and WiFi are also available. This test-bed has been selected because it fits perfectly with the definition of open-mall, shops core in indoor-outdoor with mixed localization available.

We have used our app to train and test the BAI4SOW software framework running in three different mobile devices, two smartphones: Samsung Galaxy S6 and S6 edge; and one tablet Samsung Galaxy Tab 2. Table 1 shows the 6 paths that we have considered in order to validate our system. Paths consist of 4 or 5 steps of activities that start in a tuple activity-zone-place or key point and evolve to next one. Paths are executed several times and dates to validate the results obtaining 17 paths for training (17 static places) and 35 for testing (almost 6 times per path in movement). The table also shows the approximated travelled distance at each test's path, that ranges from 250 m to 410 m. For example, **Path 00** consists of the next steps:

Table 1. Paths in shopping mall.

Path	Device	Distance	App waypoint			
			Step	Activity	Zone	Place
00	**S6/S6 E**	**300 m**	1	Eating	Restaurants	Cafetito
			2	Walking	Restaurants	No Place
			3	Walking	Shops	No Place
			4	Shop window	Shops	Poly
01	**S6**	**410 m**	1	Eating	Restaurants	Cafetito
			2	Walking	Restaurants	No Place
			3	Walking	Shops	No Place
			4	Walking	Hypermarket	No Place
			5	Buying	Hypermarket	No Place
02	**Tab2**	**250 m**	1	Eating	Restaurants	Cafetito
			2	Walking	Restaurants	No Place
			3	Walking	Outdoor	No Place
			4	Shop window	Outdoor	McDonalds
			5	Buying	Outdoor	McDonalds
03	**Tab 2/S6**	**300 m**	1	Shop window	Restaurants	Cafetito
			2	Walking	Restaurants	No Place
			3	Walking	Shops	No Place
			4	Shop window	Shops	Poly
04	**Tab 2/S6 E**	**410 m**	1	Shop window	Restaurants	Cafetito
			2	Walking	Restaurants	No Place
			3	Walking	Shops	No Place
			4	Walking	Hypermarket	No Place
			5	Buying	Hypermarket	No Place
05	**S6/S6 E**	**250 m**	1	Shop window	Restaurants	Cafetito
			2	Walking	Restaurants	No Place
			3	Walking	Outdoor	No Place
			4	Shop window	Outdoor	McDonalds
			5	Buying	Outdoor	McDonalds

S6: Samsung Galaxy S6
S6 E: Samsung Galaxy S6 Edge
Tab 2: Samsung Galaxy Tab 2

1. Activity *Eating* (having the breakfast) at *Place* Cafetito in *Restaurants* zone during 20 min.
2. Activity *Walking* along *Restaurants* zone during 2 min.
3. Activity *Walking* along *Shops* zone during 5 min.
4. Activity looking at *Shop window* of Poly *Place* at *Shops* zone during 4 min.

Fig. 4. Open mall CC Dehesa.

This path took us about 300 m of travelled distance and at about 31 min. As you can see, the difference between activities 2 and 3 is the zone, key information that we obtained from the localization system.

The summary of high level activities that we have added to the basic activities recognized by the google's API are:

- Eating: we suppose that person is eating when he/she is localized at a restaurants zone during a higher time than a threshold.
- Walking: accelerometers and localization are key features to determine that person is walking.
- Shop window: this activity means that a person is standing at the front of a shop but lower time than a threshold.
- Buying: localization is key feature to determine that person is buying inside a shop or hypermarket.

These high level activities will help us to elaborate automatic reports in a short future work. As we stated before, localization information is a key feature to determine when a change in activity is detected. This information joined with accelerometers can be crucial to infer the pattern of activities as we will shown in the next sections.

4.3 User Behavioural Analytics Results

In this section we describe how we apply process mining techniques to the activity and localization data obtained and described in the previous sections, aiming to discover and analyze the behaviour of the mall customers. The analysis starts with an event log containing the activities performed by all the customers—formed by multiple executions of the 6 paths described in Table 1. Later, we discover a graph composed by these activities—nodes—and the relations—directed arcs—between them—i.e., a process model. Finally, using this process model, the users behavioral analytics conducted are extracted to understand better how they behave. Among these analytics, a search of commonly executed behavioral activity patterns—sets of activities, and the relations between them—is performed.

Process mining is a research field offering techniques to discover, analyze and enhance processes inside an organization [2]. In this case, we consider the behavior of the customers in the mall as the process to analyze, and the activities that each user carries out while in the mall are the execution of the process. The starting point is an event log storing the activities each customer performs, the instant in which they have been executed, and the customer ID. This event log has been generated with the information collected by the smartphone application, described in Sect. 4.1, which has recorded the activities of the customers inside the mall. With this event log, a process discovery algorithm is applied to discover the process model depicting the behavior of the customers (Fig. 4).

As discovery algorithm we used ProDiGen [8]. ProDiGen is a genetic discovery algorithm searching for complete, precise and simple process models. The result of applying ProDiGen to the recorded event log is depicted in Fig. 5, where the behavior of the customers in the mall can be observed.

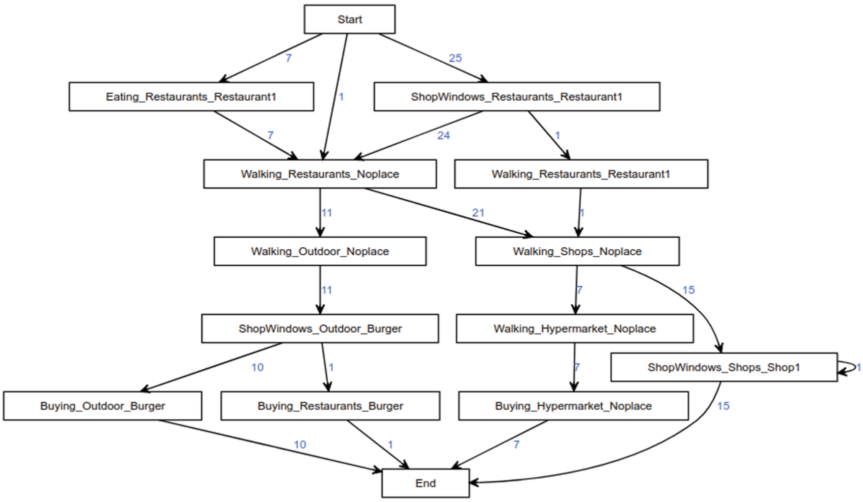

Fig. 5. Process model discovered by ProDiGen [8] depicting the behavior of the customers in the mall.

With this model some information about the behavior of the customers can be extracted: the customers who walk through the restaurants zone, go outdoors, and stop in the front of the shop window of the burger, mostly buy in the outdoor burger. To extract more information, a simplification in the event log can be done removing the paths which can be considered as 'noise', i.e. those executed only by one customer.

Figure 6 shows the process model of the customers behavior without the 'noise' of those single executions, and the relations between the activities of this model colored depending on their frequency. We can see that the most common actions are *i)* start in the shopwindow of Restaurant 1, *ii)* go walking from there through the restaurants zone, and *iii)* walk from the restaurant to the shops zone. Nevertheless, this information does not ensure a causality between these events. For instance, we cannot know if the customers who walk in the shops zone come from activity `Eating_Restaurants_Restaurant1` or from `ShopWindows_Restaurants_Restaurant1`. This information is crucial in the decision making step to select the best decisions to improve the marketing campaign inside the mall.

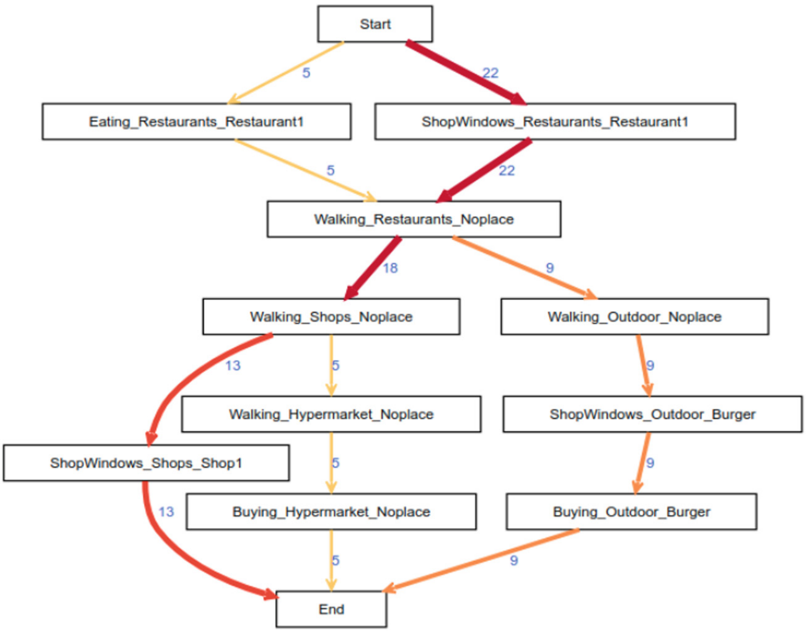

Fig. 6. Process model, discovered with the simplified event log, and with the arcs highlighted depending on their absolute frequency—thicker and a darker color implying a higher frequency.

To obtain this information, WoMine [4] has been used to extract the frequent activity patterns modeling the behavior commonly executed by the users. WoMine is an algorithm that searches, in the process model, for frequent activity

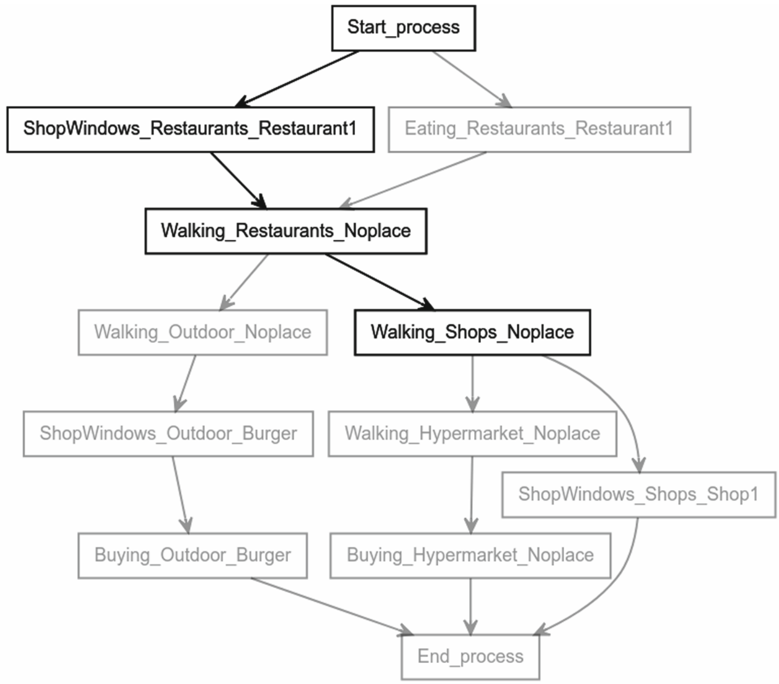

Fig. 7. Frequent pattern (highlighted structure) modeling the behavior performed by a 49% of the customers.

patterns—subgraphs of the process model ensuring all the structure it models has been executed frequently. Figure 7 highlights a behavioral pattern with a frequency of 49%, extracted with WoMine. This behavior has been conducted by the 49% of the recorded customers, who have started in the shopwindow of the Restaurant 1, walking through the restaurants and the shops either ending buying in the hypermarket or passing through the shopwindow of Shop 1. This can hint the need of Restaurant 1 to make changes in order to engage more of the customers who stop at its shopwindow but leave to other areas, without entering in it. Figure 8 depicts another behavioral pattern being executed also by the 49% of the customers. This pattern shows that half of the customers pass walking through the restaurants and shops zones, leaving the mall after staring to the shopwindow of Shop 1. This hints that it might be also interesting to work on the ads at the more frequented zones, Restaurants and Shops, to deal with those customers who leave the mall without consuming anything.

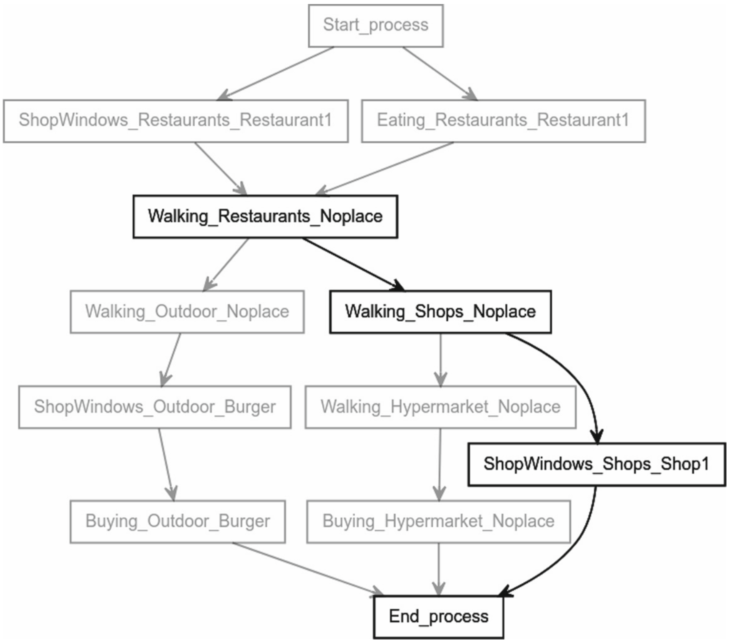

Fig. 8. Frequent pattern (highlighted structure) modeling the behavior performed by a 49% of the customers.

5 Conclusions and Future Works

We have presented a method to estimate the activity patterns made by shoppers in open malls based on localization data. Such data are provided by a specific smartphone application for logging information from sensors and process mining techniques to identify what kind of usual activity patterns are made by the shoppers. We use the localization key information joined with data mining, parallelization and monitoring techniques.

Our system has been tested in a challenging real scenario such as open mall (mixed classical mall and isolated shops in the street) where location is obtained by mean of Global Positioning System (GPS) and a WiFi localization system that is helped by a parallel computing method to speed up the whole process. From these localization data, we apply state of the art process mining techniques to first generate a process model (social workflow) describing the behavior made by the shoppers in the mall. We have also analyzed the most common activity patterns performed by the users. The hints provided by these process mining techniques may help mall's managers to take specific actions considering the customers behaviour and the activities they perform while in the mall.

As future work, we will address the integration of the process-to-text module, which automatically describes in natural language the most relevant characteristics of the customers behaviour, providing complementary information to the one conveyed by the visualization of the process models.

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