Comparative Sequential Pattern Mining of Human Trajectory Data Collected from a Campus-wide BLE Beacon System

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***Abstract*—Many social issues are expected to be addressed by collecting human trajectory data and analyzing them. As a demonstration study, we need a continuous and instant localization and trajectory collection system. We have developed a localization system using Bluetooth Low Energy (BLE) beacons and smartphones in our college campus. The system has been established to realize automated student roll call with 1,600 BLE beacon emitters installed on our campus. We can estimate the location of a smartphone in our campus by analyzing received BLE beacons and their RSSIs (Received Signal Strength Indicators). In this paper, we demonstrate how we collect human trajectory data and how we can detect specific human behaviors from the collected data. We have obtained human trajectory data from 169 research participants comprised of 671 trips during the study held as a college festival event. Each research participant walked around with his/her smartphone. The smartphone continuously received BLE beacons during the event and periodically sent them to the server as a trajectory. We apply comparative sequential pattern mining to the obtained trajectory data and extract sequential patterns that are different between male trajectories and female trajectories. This study demonstrates the effectiveness of human trajectory data collection by a BLE beacon system and data analysis by comparative sequential pattern mining.**

***Index Terms*—Bluetooth Low Energy beacon, position estimation, PrefixSpan, S3P-classifier, trajectory mining**

I. Introduction

Many animals, including humans, moves around for their variety of purposes. Recent development of location measurement technology allows us to collect trajectory data, and such data can be used for characterizing, understanding, and predicting animal navigation behaviors. Our research group is working on systematic understanding of animal navigation behavior. The goal of this study is to demonstrate the effectiveness of human trajectory data collection by BLE (Bluetooth Low Energy) beacon system and data analysis by comparative sequential pattern mining for such purpose.

In recent years, the importance of location information has been recognized. Various kinds of knowledge and applications such as mapping and navigation have been derived from location information. Although "one time" location information is useful for these applications, social significance of "continuous" location information is increasing for behavior analysis or anomaly detection. Continuous location information is called as trajectory data. Improvement of devices and development of communication technology make it easier to collect trajectory data. Many studies aim to estimate the location, collect and store trajectory data, analyze and utilize the movement behavior of humans and animals. In order to measure and analyze trajectory of humans or animals, we need a system to collect and store location information.

In general, location can be estimated by using GPS (Global Positioning System), location of landmarks such as base stations of a cellular network or public access points of wireless LAN, or geographical information of beacons. However, in college or university campus in which buildings are densely arranged, accuracy of location estimation is low because of reflections, diffractions, interferences, and attenuations of radio waves. Estimation error could be in the order of several tens of meters in the above environment. Therefore, it is difficult to measure the accurate position of a moving person within an error of several meters, which is minimum requirements to track human walking behavior.

In our college, we have been operating an automated student roll call system for several years. The system can decide within a few seconds in which classroom or corridor a student's smartphone is located. Such an indoor position estimation can be realized by using BLE beacons and their RSSIs (Received Signal Strength Indicators). About 1,600 BLE beacon emitters have been densely installed in and around classrooms at our college. By conjunction of installed location of the BLE beacon emitters and RSSI of received BLE beacons, it

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is possible to estimate the indoor position with an error of several meters. It becomes possible to collect human trajectory data by using this BLE beacon system.

In this paper, we introduce a human trajectory data collection system using the BLE beacons in our campus. To analyze human trajectory data, we adopt comparative sequential pattern mining, which can find different characteristics between distinct groups of trajectories. Comparative sequential patterns are extracted by learning of linear classification model. The problem of learning comparative pattern-based classifier is formulated as a convex optimization problem. However, since the number of patterns are exponentially large, conventional optimization algorithms cannot be used straightforwardly. We use S3P-classifier [1] to cope with exponentially increasing patterns. We can efficiently search patterns which are useful for differentiating distinct groups of trajectory data by S3P-classifier.

In this study, we collected human trajectory data from 169 research participants comprised of 671 trips during the experiment held as a college festival event. Participants were requested to go to certain destinations by referencing the "estimated distance to the destination" indicated in their smartphones. We applied comparative sequential pattern mining to the collected human trajectory data, and extract sequential patterns that are different between male trajectories and female trajectories. From this demonstrative study, we found patterns indicating that the male participants tend to move straight while the female participants seem to move slowly compared to male.

The rest of the paper is organized as follows. We address related work in Section II and explain how we collect human trajectory data in Section III. Then we show trajectory data symbolization and comparative sequential pattern mining in Section IV. The results of comparative sequential pattern mining are shown in Section V, then we conclude the paper in Section VI.

II. Related work

Various position measurement systems have been developed due to improved processing capability of the device, miniaturization and power saving, and development of communication technology. As a result, it has become possible to measure movement trajectories of humans, things, and animals. In addition, there are many attempts to analyze the measured trajectory data and to extract knowledge on the movement behavior.

Location estimation

There are several methods for location estimation based on RSSI. Fingerprinting methods [2]–[4] have some tolerances to environmental noise, but the methods have to pre-construct fingerprint dictionary. Trilateration methods [5]–[7] calculate the location by coordinates of known landmarks, thus the methods are suitable if enough number of landmarks are installed.

In our college, we have been operating an automated student roll call system for several years. The system can estimate within a few seconds in which classroom or corridor a student's smartphone is located. A floor level of a smartphone can be determined correctly [2]. The system consists of BLE beacon emitters, a smartphone, and servers which estimates and stores current location of the smartphone. Each BLE beacon emitter sends a BLE beacon periodically. When a student taps the button on the dedicated app (application software running on smartphones) installed on a smartphone, the smartphone receives BLE beacons for $3\,\mathrm{s}$ and sends them to the frontend server. Each beacon contains emitter's ID. The smartphone measures RSSI of each beacon. Based on the ID and the RSSI, the position of the smartphone is estimated at the server with an error of several meters. Since we have installed the BLE beacon emitters on almost all floors and it is hard for BLE beacons to go through floor materials, the system can estimate floor level correctly. In this study, we used this BLE beacon system to collect data of human trajectories when they walk around within our campus.

Trajectory measurement

Many attempts have been made to capture and analyze moving behavior for humans and animals. There are an individual classification approach [8] and an individual detection approach [9] to capture movement behavior. The individual classification approach [8] generally needs a video or a series of pictures as an input. The input is processed for target identification, motion detection, and target tracking. The approach can be adopted on occasions such as tracking in local area or roughly counting number of targets. When we need precise individual classification and tracking in wide area where a camera cannot cover the whole area, the approach is not suitable. The individual detection approach [9] needs dedicated mark or device, which is necessary to detect and classify individuals. To achieve position tracking of individuals sequentially and simultaneously, each individual and a system should have a positioning device which has a unique sender or receiver ID. For this purpose, we can use the BLE beacon emitters as senders and smartphones as receivers.

Comparative sequential pattern mining

Most of pattern mining studies are aimed at extracting frequent patterns [10], [11]. Among several pattern mining types, sequential mining can be effectively used for trajectory data analysis [12], [13]. Yang et al. proposed a bidirectional pruning based sequential pattern mining algorithm [14]. By employing tree structures to create partitions of input sequences and candidate patterns, closeness can be checked efficiently and the algorithm outperforms three other state-of-the-art algorithms on a large GPS dataset with more than 600,000 taxi trip trajectories.

We consider comparative sequential pattern mining in our study. Comparative sequential pattern mining is a pattern mining method which may derive difference between distinct groups of trajectory data. In the case of human trajectory data analysis, groups can be, for example, gender, age, presence or absence of a certain symptom, and so on.

In general frequent sequential mining methods, differences between distinct groups are not considered. In this paper, we adopt the method of Sakuma et al. [1], which can construct a classification model from appearance of certain patterns, and try to extract characteristic patterns by constructed classification model.

III. Collection of human trajectory data

By using our BLE beacon system, we can estimate position more accurately and precisely than GPS or other public location systems. In this section, we describe what kind of tasks were imposed on research participants in collecting purpose-oriented indoor/outdoor human trajectory data. We also describe the BLE beacon collection system and the position estimation method required for accurate trajectory analysis.

A. Human movement task

In order to collect purpose-oriented data, we set tasks for research participants to move to virtual destinations (referred to as "GOALs") set in advance by experiment conductor. Each participant starts and ends a task by manipulating his/her smartphone (mobile device). When a participant starts a task, estimated distance from current position to the GOAL of current task is indicated on his/her smartphone. During the task, estimated distance from the current position to the GOAL is updated periodically. The update interval is set to $2\,\mathrm{s}$ in the study. The position estimation method is described in Section III-C. The participant searches the appropriate GOAL by walking with reference to the estimated distance to the GOAL indicated on the smartphone. A task can end by tapping the button which appears while the smartphone is close to the GOAL (within $20\,\mathrm{m}$ from the GOAL). Each participant performs this task 5 times. The GOALs of 5 tasks are not duplicately selected by experiment conductor. There is no landmark in the real world that indicates GOALs.

B. BLE beacon collection system

Human trajectory data is collected by the BLE beacon collection system. As shown in Fig. 1, the system consists of a smartphone, BLE beacon emitters, and servers. A smartphone must handle BLE functions. Each BLE beacon emitter periodically sends a BLE beacon which contains its own ID. When a smartphone receives a BLE beacon on the dedicated app, the app constructs a "beacon information," which consists of the received beacon, reception timestamp, and RSSI of the beacon. The app periodically sends beacon information to the frontend server. The sending interval is set to $2\,\mathrm{s}$ in the study. The app having the above functions are developed each for iOS and Android and installed to participants' smartphones. Due to limitation of mobile OS on some models, the smartphone may stop receiving beacons and sending beacon information when a smartphone enters into sleep mode. However, while the app is running and the screen is on, i.e., while a participant is checking the estimated distance to the GOAL indicated on the screen, beacons are surely collected and beacon information is sent to the server. In addition, the app has a resend function. Even if the app fails to send beacon information, it tries to resend while the app runs.

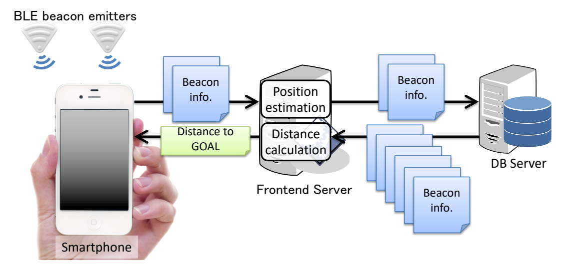

Fig. 1: BLE beacon collection system with position estimation and distance calculation modules.

The frontend server receives beacon information from smartphones and stores it to the database server. The beacon information is used by position estimation module and distance calculation module on the frontend server. The frontend server calculates the estimated distance to the GOAL and send it back to the smartphone. Then, the app indicates the estimated distance to the GOAL.

C. Location estimation from beacon information

Beacon information sent from a smartphone is stored in the database server. The frontend server estimates current location of the smartphone with accumulated beacon information. Current position of a smartphone can be estimated accurately and precisely even when the smartphone is in a building.

As we mention in Section V, localization method adopted in the experiment is chosen by a game event promoter. In this study, the required accuracy and frequency of position estimation are not so high, i.e. several meters and several seconds, respectively. Thus, we approved the weighted centroid localization (WCL) method [7], which is known as simple, flexible, and low calculation cost position estimation method. Depending on various factors such as environment conditions and geographical characteristics of locations of the BLE beacon emitters, a smartphone may receive some beacons far away by chance while it cannot receive other nearer beacons. Therefore, we investigated the transmission range of all beacon emitters and set the weight of each of them.

TABLE I: Example of raw data and symbolized data. Former symbol N: `normal`, W: `wandering`; Latter symbol D: `down` (distance to GOAL is decreased), U: `up` (distance to GOAL is increased).

Received datetime	Longitude	Latitude	Distance to GOAL	Symbol
2017-11-24 11:54:20.176	136.924149	35.156740	52	(N, D)
2017-11-24 11:54:22.210	136.924157	35.156749	51	(N, D)
2017-11-24 11:54:24.240	136.924193	35.156742	47	(N, D)
2017-11-24 11:54:26.289	136.924186	35.156772	47	(W, D)
2017-11-24 11:54:28.262	136.924299	35.156746	37	(W, D)
2017-11-24 11:54:30.305	136.924408	35.156769	26	(N, D)
2017-11-24 11:54:32.335	136.924538	35.156815	15	(N, D)
2017-11-24 11:54:34.375	136.924497	35.156782	19	(W, U)
2017-11-24 11:54:36.443	136.924563	35.156845	12	(W, D)
2017-11-24 11:54:38.500	136.924561	35.156825	14	(W, U)

IV. Data symbolization and comparative sequential pattern mining

For comparative sequential pattern mining, it is necessary to represent a trajectory by a sequence of symbols. In this section, we describe a data symbolization method in Section IV-A and a comparative sequential pattern mining method in Section IV-B.

Notation: We use the following notation in the rest of the paper. For any natural number n, we define $[n] := \{1, \ldots, n\}$. For an n-dimensional vector $\boldsymbol{v}$ and a set $\mathcal{I} \subseteq [n]$, $\boldsymbol{v}_{\mathcal{I}}$ represents a sub-vector of $\boldsymbol{v}$ whose elements are indexed by $\mathcal{I}$. The indicator function is written as $I(\cdot)$, i.e., $I(z) = 1$ if z is true, and $I(z) = 0$ otherwise. The L_1 norm of a vector $\boldsymbol{v}$ is written as $\|\boldsymbol{v}\|_1$. A sequence (an ordered list of discrete symbols) with length T is represented as $\langle g_1, g_2, \ldots, g_T \rangle$.

A. Data symbolization method

In order to apply comparative sequential pattern mining to the collected trajectory dataset, we need to symbolize the data. First, we classify human movement to 3 states: `stop`, `move`, `turn`. A movement state is determined from speed and direction of a trajectory. Speed and direction are derived by calculating difference of current and previous records. `Stop` state indicates that speed is less than $0.2\,\mathrm{m/s}$. `Turn` state indicates that speed is at least $0.2\,\mathrm{m/s}$ and heading direction changes at least 90° from previous direction. Otherwise, `move` state is assigned. We integrate the above 3 states into `normal` and `wandering` states: if `move` state continues more than $4\,\mathrm{s}$, we define the continuously moving state as `normal`, otherwise as `wandering`.

We also symbolize "distance to GOAL" of each record of trajectory data since each research participant makes a decision by considering the distance to the GOAL indicated in his/her smartphone. In this paper, we calculate a distance to GOAL as described in Section III-C, and classify transition of the distance to GOAL into `up` (increasing) and `down` (decreasing) states.

We combine the above movement and distance states into one unified symbol. We describe movement symbols as N (`normal`) or W (`wandering`) and distance symbols as U (`up`) and D (`down`). The unified symbol is described by combination of movement and distance symbols as shown in the "Symbol" column of Table I. Table I shows an example of raw data and corresponding unified symbol.

B. Comparative sequential pattern mining method

In this paper, we extract patterns that can express differences between groups by learning of linear classification model. The training set is written as

$$\{(\boldsymbol{g}_i, y_i)\}_{i \in [n]},$$

where $\boldsymbol{g}_i$ represents the i-th sequence, and $y_i \in \{\pm 1\}$ represents the label of each group, e.g., male or female. We represent a case where a sequence $\boldsymbol{g}_i$ contains a pattern $\boldsymbol{q}_j$ as $\boldsymbol{q}_j \sqsubseteq \boldsymbol{g}_i$. We introduce a classifier based on a sparse linear combinations of patterns

$$f(\boldsymbol{g}_i; \mathcal{Q}) := \sum_{\boldsymbol{q}_j \in \mathcal{Q}} w_j I(\boldsymbol{q}_j \sqsubseteq \boldsymbol{g}_i) + b, \tag{1}$$

where $w_j \in \mathbb{R}$ and $b \in \mathbb{R}$ are the parameters of the linear model. We estimate these parameters by solving the following minimization problem

$$\min_{\boldsymbol{w}, b} \sum_{i \in [n]} \ell(y_i, f(\boldsymbol{g}_i; \mathcal{Q})) + \lambda \|\boldsymbol{w}\|_1, \tag{2}$$

where $\boldsymbol{w} := [w_1, \ldots, w_d]^\top$, $\ell : \mathbb{R} \times \mathbb{R} \to \mathbb{R}$ is a loss function, $\mathcal{Q}$ is the set of all possible patterns contained in any one of the sequences, and $\lambda > 0$ is a tuning parameter. If the loss function is the so-called squared hinge-loss function defined as $\ell(y, f(\boldsymbol{x}_i)) = \max\{0, 1 - yf(\boldsymbol{x}_i)\}^2$, the optimization problem shown in (2) is in the form of L_1-penalized squared hinge-loss support vector machine (SVM).

If the weight of each feature quantity after learning of the linear classification model is positive, it is a characteristic pattern for group $+1$, whereas if it is negative, it is considered to be a characteristic pattern for group -1. We note that existing optimization algorithms for sparse learning cannot be used for solving the minimization problem shown in (2) since the number of patterns $|\mathcal{Q}|$ is quite large. For example, the number of different symbols in this paper is $2 \times 2 = 4$, and if subsequence patterns of up to length 50 are considered,

TABLE II: Comparative sequential pattern extraction results of male and female. We note here that w_j means weight value revised by S3P-classifier method and $support$(Male/Female) means total value of support in trips with Male/Female group. The pattern $(\mathrm{N}, \mathrm{D}) \times 12$ means (N, D) continues 12 times.

Pattern	w_j	$support$ (Male)	$support$ (Female)
$\langle(\mathrm{N},\mathrm{D}),(\mathrm{N},\mathrm{U})\times 7\rangle$	0.209205	59	23
$\langle(\mathrm{N},\mathrm{D})\times 6,(\mathrm{W},\mathrm{U}),(\mathrm{W},\mathrm{D})\rangle$	0.099198	105	83
$\langle(\mathrm{N},\mathrm{D})\times 12\rangle$	0.085648	117	72
$\langle(\mathrm{N},\mathrm{D}),(\mathrm{N},\mathrm{U})\times 5\rangle$	0.049365	84	48
$\langle(\mathrm{W},\mathrm{U})\times 2,(\mathrm{N},\mathrm{D})\times 3\rangle$	0.037740	75	76
⋮	⋮	⋮	⋮
$\langle(\mathrm{W},\mathrm{D}),(\mathrm{W},\mathrm{U})\times 2,(\mathrm{W},\mathrm{D}),(\mathrm{W},\mathrm{U})\times 2\rangle$	-0.135921	36	82
$\langle(\mathrm{N},\mathrm{U}),(\mathrm{N},\mathrm{D}),(\mathrm{W},\mathrm{U}),(\mathrm{W},\mathrm{D})\rangle$	-0.140238	31	76
$\langle(\mathrm{W},\mathrm{D}),(\mathrm{N},\mathrm{D}),(\mathrm{W},\mathrm{U})\rangle$	-0.149705	7	48
$\langle(\mathrm{W},\mathrm{U}),(\mathrm{W},\mathrm{D}),(\mathrm{N},\mathrm{D}),(\mathrm{N},\mathrm{U})\rangle$	-0.194924	44	95
$\langle(\mathrm{W},\mathrm{U}),(\mathrm{N},\mathrm{U}),(\mathrm{W},\mathrm{D})\rangle$	-0.237658	4	44

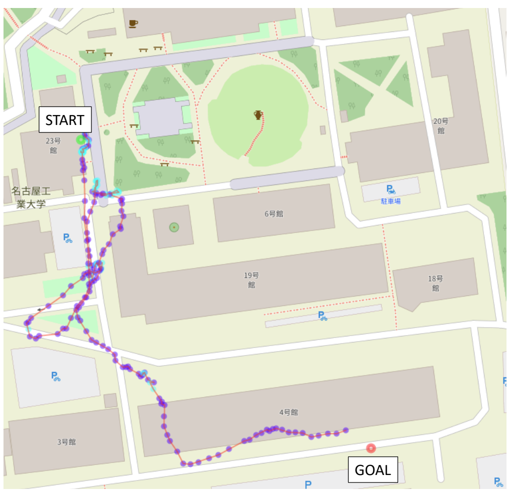

Fig. 2: An example trip of a male participant. Each circle corresponds to the following point: green: starting point of the trip, red: GOAL point, purple: estimated point of `normal` state, aqua: estimated point of `wandering` state. The participant took many straight lines pointed as a sequence of normal states.

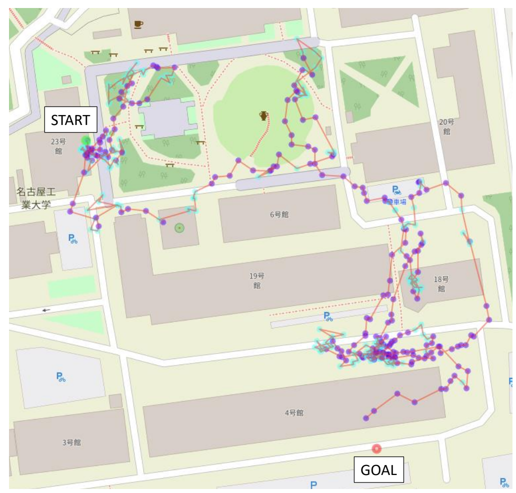

Fig. 3: An example trip of a female participant. Each circle corresponds to the description on caption of Fig. 2. The participant took various ways pointed as some wandering states indicated by aqua points.

$|\mathcal{Q}| = 4^{50} \fallingdotseq 1.3 \times 10^{30}$. The maximum pattern length L is a hyperparameter, and it is preferable to set it as large as possible since it is not known what kind of pattern is characteristic of the group. In this paper, we use S3P-classifier [1] as a method to cope with exponentially increasing features. S3P-classifier can identify and eliminate unnecessary features in the optimal model before optimization by using a technique called safe screening [15], [16]. In S3P-classifier, a pattern is searched by sequence mining with PrefixSpan [12], and whether or not the pattern is unnecessary is judged by using a feasible solution at that time. PrefixSpan is an algorithm for searching with depth priority while gradually increasing the sequence length. If the pattern is judged to be necessary, the search of the pattern is continued. However, if the pattern is judged to be unnecessary, the branch of the pattern is pruned and the other branch of the pattern is searched. After going through the entire search, the weight w_j is learned by solving the optimization problem shown in (2). By the L_1 regularization term, many w_j becomes 0, and only small subset of patterns that contribute to the classification model have non-zero w_j. In this paper, we extract the pattern with non-zero w_j as a characteristic pattern.

V. Experiment and Results of Comparative Seqiential Pattern Mining

At the college festival held for 2 days from November 24 to 25, 2017, a positioning game was held by C0de, an official club of our college. We entrust them with the game event and the localization method related to the game. With the consent of positioning game participants, human trajectory data was collected and accumulated in the server while they were playing the game. There were

169 (male: 112, female: 56, unanswered: 1) research participants comprised of 671 (male: 474, female: 197) trips during the college festival event. The GOAL is about $200\,\mathrm{m}$ away from each of the starting positions and each participant walked by the side of or through the college buildings. Some participants worked in groups.

In this experiment, we analyzed male as group $+1$ and female as group -1. We picked 197 samples from 474 male trips at random to make up the number of male and female trips. The hyper parameter λ in the optimization problem shown in (2) was determined by 10-fold cross-validation.

A. Results of comparative sequential pattern mining

Table II shows the sequential patterns whose coefficients in the optimal model are nonzero. 37 patterns are extracted. Table II only shows a part of the extracted patterns due to the space limitation. From the result, we found characteristic patterns of male behavior that the symbols (N, D) and/or (N, U) chain many times, i.e., men tend to keep on moving straight. We also found characteristic patterns of female behavior that the symbol (W, U) chains or both (W, D) and (W, U) appears, i.e., women seemed to move slowly compared to men.

Figs. 2 and 3 are example trips of male and female participants, respectively. Both trips have been set the same starting and GOAL points. As shown in these figures, the male participant took many straight lines and most of the straight lines tend to approach to the GOAL while the female participant took various ways and wandered the streets. We confirmed that these gender-specific trajectory characteristics are also shown in many other trips. This is the reason why we can get the above results of comparative sequential pattern mining shown in Table II.

VI. Conclusion

In this paper, we introduced the human trajectory data collection system and demonstrated comparative sequential pattern mining. The system can collect continuous human trajectory data with an error of several meters. In cooperation with 169 research participants, we could collect 671 purpose-oriented trips during the study held as a college festival event. By applying comparative sequential pattern mining, we could extract sequential patterns that are different between male trajectories and female trajectories. We found characteristics of male and female behavior that male participants tend to keep on moving straight while female participants seem to move slowly compared to male.

We could not discuss the significance of the derived patterns theoretically. We should take a numerical analysis to discuss the performance of the classifier. We are trying to extract characteristics of other kinds of groups by other symbols or labels, e.g., groups: finally reached the GOAL or not, symbols: `keep_moving` or `stop`, labels: student or working adult.

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