Easy-to-Deploy Living Activity Sensing System and Data Collection in General Homes

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***Abstract*—Emergence of smart appliances and high performance IoT devices is promoting studies on more functional and intelligent home services using these devices. Especially, in developed countries including Japan with aging population and declining birthrate, it is urgent to develop technologies to monitor living situations of residents including elderly persons and improve their quality of life (QoL) through home services based on the activity recognition technology. However, activity recognition systems in general require many types/number of sensors and hence they are difficult to deploy and operate. In this paper, we propose a system consisting of low-cost and easy-to-deploy sensors based on energy harvesting that can collect data of resident's activities of daily living (ADL) for months without maintenance. The system was deployed in 10 homes of senior citizens where we collected ADL data for two months each. We also estimated the ADLs from the collected data by using long short-term memory (LSTM), a deep learning model. As a result, ADLs could be estimated at high recall rate of 82.4% on average and hence we found that the proposed system has high applicability to actual services.**

***Index Terms*—daily activity recognition, IoT, machine learning, LSTM, simple installation sensing system**

I. Introduction

Society 5.0[1], a human-centered society that balances economic advancement with the resolution of social problems by a system that highly integrates cyberspace and physical space, was proposed in the 5th Science and Technology Basic Plan as a future society that Japan should aspire to. To realize Society 5.0, Cyber-Physical System (CPS) must be spread in various fields and locations [1]. CPS aims to provide higher-quality services and/or solve industrial problems by sensing/collecting data in real space and storing/accumulating the collected data in cyberspace with IoT and ICT technologies.

On the other hand, aging is a serious problem in many countries. In suburbs and residential areas, aging is progressing at a rate earlier than the average aging rate [2]. Therefore, it is urgent to take effective plans for (1) monitoring and nursing for elderly people, and (2) encouraging healthy behavior for them. In order to solve the above issues, many studies utilizing activity recognition technology have been conducted to make improvements in lifestyles of residents and provide an elderly monitoring service. However, most of the exiting CPS-based activity recognition systems are realized/tested only in experimental environments. Few systems have been designed to collect and analyze data in real households yet. To install a CPS system in ordinary homes, we must consider many factors such as installation cost, privacy protection and system robustness.

In this paper, to solve the issues (1) and (2), we propose a system consisting of low-cost, easy-to-deploy and low-maintenance cost sensors based on energy harvesting that can collect data of resident's activities of daily living (ADL) for months without maintenance. The system was deployed in 10 homes of senior citizens where we collected ADL data for two months each. We also estimated the ADLs from the collected data by using long short-term memory (LSTM), a deep learning model. As a result, ADLs could be estimated at high recall rate 82.4% on average. Consequently, the applicability to actual services was confirmed.

II. Related Work

This section describes existing studies on sensing systems in home and ADL recognition methods. There are a variety of studies on sensing systems such as an efficient edge computing system that reduce communication overhead by data prediction [3], activity sensing system for elderly people using voice call [4], real-time activity sensing system using indoor positioning sensor and power meters [5], a wireless sensing system that collects data securely [6], and the method on transferring data between different homes by remapping features obtained each home into the same space [7].

Additionally, there have been proposed many methods that provide residents with the results and the knowledge acquired by sensing, for example, a method to increase resident's quality of life (QoL) by using feedback from users [8], [9]. However, most of these existing systems or methods are designed and experimented only in experimental environments, not in the actual environments. Hence, their applicability to actual general homes in terms of cost, robustness, etc are not clear.

Wan et al. [10] have analyzed data collected from a wireless network designed by themselves in a smart home to recognize ADLs. The sensors used for collecting data are infrared sensors for detecting occupants, pressure sensors in chairs, temperature/illuminance/water amount sensors for measuring the ambient environment, TV usage information, magnetic door sensors, smoke detection sensors and wearable accelerometers worn by residents. An activity recognition method by Bayesian Network (BN) and Hidden Markov Model (HMM) has been proposed using the data collected from those sensors. As a

[1] https://www8.cao.go.jp/cstp/english/society5_0/index.html

result, it has been shown that daily activity recognition is possible with high accuracy 91.2% by BN. On the other hand, the sensors themselves are not very expensive, but their deployment/maintenance costs are rather high and wearable devices are intrusive to residents.

Sasaki et al. [11] have proposed an ADL recognition method using ECHONET Lite appliances, infrared sensors and ultrasonic position estimation system in smarthome. Nine types of daily activities are recognized by the models trained with the sensor data including On/Off state of appliances, infrared sensors, door sensors and environmental sensors. As a result, activities are recognized with accuracy of 85.8% by random forest, 84.9% by logistic regression, and 81.5% by LSTM. The method is able to recognize resident's activity with high accuracy, while the system requires ECHONET Lite-compatible appliances and expensive ultrasonic positioning sensors in the home, hence it is difficult to spread to general homes.

Marufuzzaman et al. [12] have predicted a next resident's activity by considering episodes of the resident. For the purpose, they used the algorithm called SPEED based on Prediction by Partial Matching (PPM) to estimate the episodes from appliance usage information. They collected the data of appliances such as room lighting, television, ceiling fans, cookers and toasters. Furthermore, as the target data, they divided activity log of one resident into morning and afternoon sessions. As a result, it was confirmed that the prediction accuracy was improved in a specific floor plan of a home such as home with only a single room. This method has room to improve the prediction accuracy by introducing additional sensors. However, it would be difficult to spread this system to general homes since introducing multiple networked appliances is expensive.

Tax [13] has predicted resident's activity using three open datasets of smarthome: MIT, CASAS and Kasteren, by using deep learning models that can handle time series data such as LSTM and Gated Recurrent Unit (GRU). These datasets comprise the data of rather inexpensive sensors such as infrared sensors, magnetic door sensors, illuminance sensors and temperature sensors. The prediction accuracy of the next activity is 26.9% to 52.9%, and the average absolute error of the predicted time until the next activity is 1210.32 sec to 3757.70 sec. The model learns the type and time of the next activity individually, hence it only evaluates the probability that a specific activity will occur after a certain time. Moreover, prediction performance at homes with different floor plans is not evaluated.

To recognize activities by multiple residents, multi-label classification using Classifier Chain (CC) [14] and learning models using Recurrent Neural Network (RNN), HMM and Conditional Random Field (CRF) applying to CASAS and ARAS open datasets [15] were proposed. However, both methods use the datasets of smart-home with special equipments, not general homes.

As shown above, existing activity recognition and prediction methods are evaluated by analyzing the data collected in experimental environment. Therefore, in order to provide ordinary homes with the activity data collection/analysis system, it is necessary to design and develop a low cost and easy-to-deploy system that targets ordinary homes with various floor plans. Moreover, when introducing the system into a general home, it is necessary to select sensors with low deployment/maintenance costs and without violating resident's privacy.

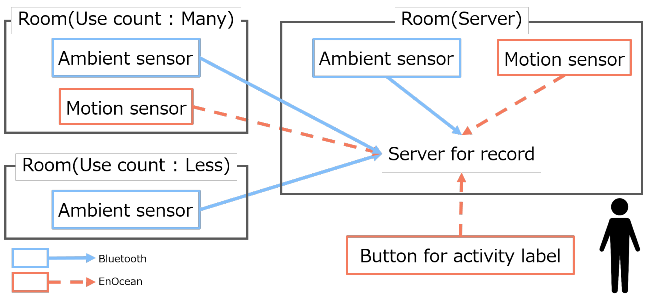

Fig. 1. Organization of ADL data collection system

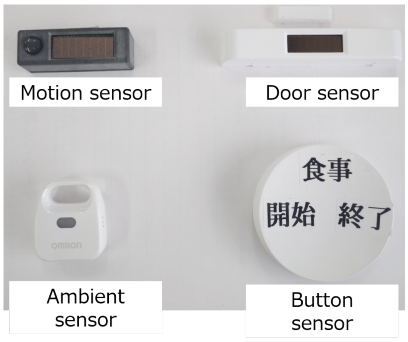

Fig. 2. Sensors used in ADL data collection system

III. ADL Data Collection System

This section describes the configuration of the proposed ADL data collection system designed for general homes. The system consists of three sensing parts: motion sensor data collection, ambient (environmental) sensor data collection and activity label collection as shown in Fig. 1. The sensors used in the system are shown in Fig. 2. The data collected by the three sensing parts, motion sensor data collection, environmental sensor collection and activity label collection is transmitted and stored in a home server (gateway) installed in the home. In our system, Intel NUC is used for the home server. The NUC is equipped with EnOcean and Bluetooth dongles for communication with sensors of Fig. 2. The NUC is also equipped with an LTE dongle PIX-MT100 so that the data collected in the NUC can be accessed remotely through local website published by ngrok.

A. Motion Sensor Data Collection

We suppose to deploy at most 10 motion sensors to a whole home and at most 1 sensor is deployed in each room/section (including kitchen, corridor, bathroom, etc). To operate for long time without maintenance, we designed and developed a motion sensor module that can perform sensing and wireless communication with the energy harvested from indoor light by using an energy harvesting module equipped with a small solar panel. ROHM's STM431J is used as an energy harvesting module, and Panasonic's EKMB1101112 is used as a motion sensor. To keep the number of motion sensors installed in a home within a fixed number (e.g., 10), motion sensors are installed in only rooms usually used.

B. Ambient Sensor Data Collection

Similarly to motion sensors, we deploy at most 10 ambient sensors in a whole home and at most 1 sensor is deployed to each room. We use Omron 2JCIE-BL01 as ambient sensor. This sensor can measure temperature, relative humidity, illuminance, UV index, atmospheric pressure, and noise. Moreover, it has Bluetooth Low Energy (BLE) wireless communication function and the sensed data can be wirelessly transmitted to the server. In our system, data on temperature, relative humidity, illuminance, atmospheric pressure, and noise are obtained. This sensor is battery-powered, and the period depends on the sampling period. In our system, the sampling period is set to 3 minutes, supposing data collection for 2 months.

C. Activity Label Collection

The activity label is obtained by questionnaire to residents and energy harvesting push button devices, ROHM's PTM 210J. This button device has two switches and a communication function based on EnOcean. It generates power when the switch is pressed and sends a packet to the server by using the generated power. In our system, five button devices are used to label five ADLs: "sleeping (going to bed/wake-up)," "cooking," "eating," "bathing," and "going out/returning home." Home residents are requested to press the button at the start and end of the corresponding activity. They can place each button device at any place where easy to press. The packet is sent when start or end of each activity is pressed at each button device. When the server receives the packet, the time of start/end of each activity is recorded.

The questionnaire is given to residents in a check sheet with a list of activities and a free description. If residents realize that they forget to press buttons on an activity, they are requested to write approximate start/end time of the activity relying on their memory. Also, if residents have unusual events such as a long trip or guest visit, they record those events.

IV. Data Collection Experiment

This section describes details of the ADL data collection experiments we conducted in general homes.

A. Experimental Conditions

We conducted data collection experiments in order to confirm if the proposed system is useful to collect and analyze ADL data in general homes where senior citizens are living. We selected 10 target elderly households over the age of 60 (3 single and 7 couples), and we collected ADL data for 2 months from each household. If the resident(s) is absent for more than one day, the experiment period is extended by the absent period so that the total number of actual stays is exactly two months.

The residents are requested to live as usual with our ADL data collection system installed in their homes, except for pressing the button at the start/end of each of five target activities (going to bed/wake-up, cooking, eating, bathing, going out/returning home) performed during their daily living. In 7 couple households, two residents share each button and press button each whenever activity is started/ended. For example, if two people start eating at the same time, the start of "eating" button is pressed twice. In addition, the resident(s) is requested, before going to bed, to answer the questionnaire described in the previous section to confirm whether they performed each of target activities and pushed the button.

B. Sensor Installation

Table I shows a list of sensors installed in each home. In this experiment, the floorplan is different among the 10 target homes. Therefore it is necessary to decide sensor installation positions for each home. We defined the following policies to install sensors in the homes:

- **How to attach/fix sensors** All sensors are fixed to the wall or door with double-sided tape. In order to protect walls and doors, we first paste a multi-purpose masking tape to walls/doors and install sensors on the masking tape with double-sided tape (Fig. 3).
- **Motion Sensor** We install motion sensor in the center of the room on the wall without curtains or other obstructions, and about 1 meter above the floor so that one sensor can cover the whole room.
- **Ambient Sensor** Ambient sensor is installed at a height of about 1 meter at any position in a room (it can be installed at the same position as the motion sensor).
- **Door Sensor** We install the door open / close sensor on the wall near the movable part of the door so that the sensor reacts when the door is closed.
- **Server** We install the sensor data collection server near the center of the home (e.g., under the sofa in living room) to keep good quality of communication with sensors.
- **Check** After completing the installation of all sensors, we check whether each sensor is working correctly (looking at the logs in the server). We remove sensors that are difficult to collect data due to shielding or installation conditions. In our experiments, we found that it was difficult to collect sensor data from door sensors in most of the homes. One possible reason is that the metal part of the door affects the measurement part inside the sensor.

In the experiment, it took approximately 30 – 45 minutes to install sensors in a home including the operation check time.

V. Analysis Method

In this section, we describe a method for understanding and analyzing the collected data. The main purpose of this work is to confirm if we can understand the life pattern of

TABLE I
SENSOR ARRANGEMENT LIST

Household ID	Kitchen	Living	Dining	Living and Dining	Washroom	Corridor	Bedroom	Toilet	Bathroom	Entrance	Other rooms
ID1	M[*i],E[*ii]	M,E	M,E	-	M	M×2,E	M,E	M×2	E	-	M,E×4
ID2	M,E	-	-	M,E	M,E	M,E	M×2,E×2	M×2	E	-	-
ID3	M,E	-	-	M,E	M,E	M×2,E×2	M,E	M	E	D[*iii]	M×3,E×3
ID4	M,E	-	-	M,E	M,E	M×2,E	M×2,E×2	M	E,D	-	M,E×2
ID5	M,E	-	-	M,E	M	M,E×2	M,E	M×2	E,D	D	M×3,E×4
ID6	M,E	-	-	M,E	M,E	M×2,E×3	M×2,E×2	M×2	E,D	D	M,E
ID7	M,E	-	-	M,E	-	M,E	M,E	M	E,D	-	M,E×2
ID8	M,E	-	-	M,E	M,E	M×3,E×3	M×2,E×2	M	E	-	M,E
ID9	M,E	-	-	M,E	M,E	M×2,E×2	M×2,E×2	M	E,D	D	M×2,E×2
ID10	M,E	-	M,E	-	E	M,E	M,E	M	E,D	D	M,E

[*i] Human sensor [*ii] Environmental sensor [*iii] Door sensor

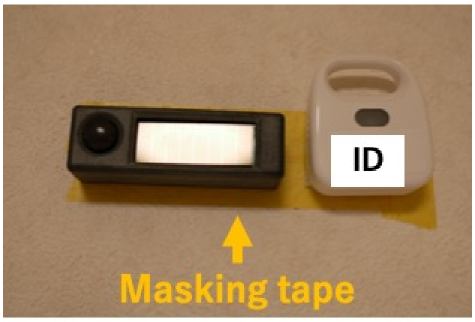

Fig. 3. Sensor installation example

the senior citizen from the data collected from general elderly households. As preliminary analysis to this end, we chose the whole data of a home with ID10 to analyze because missing data (due to forgetting of pressing buttons, etc) is relatively small and a single resident lives. The analysis results shown and discussed below are by only the data of ID10.

A. Data Preprocessing

Handling of wrong/missing data: There was a problem in annotation in the collected data. Especially, there were wrong annotations in the collected data by mistakes of pushing the wrong button for the performed activity and forgetting pressing the button when activity is performed. For instance, there was a case that a resident started eating in the morning and pressed a button but forgot to press the end button. In such a case, any flag of activity end is not sent to the system, and the eating activity label continues until the resident presses the end button for eating at noon. Therefore, when the continuous activity over the predefined threshold is observed, we regard that the interval is a mistake and that the residents did not perform any activities in the interval. Table II shows the threshold time (empirically decided) for each activity to regard as a mistake. The percentage of wrong annotations were approximately 10% of the whole data. There were few defects on the sleep activity which was the periodic activity with long duration and always performed every day, while there were many defects on the bathing activity which was performed rather irregularly. Regarding eating, cooking and going out activities, the defect rate was medium in between the sleep and bathing activities.

TABLE II
THRESHOLDS FOR EACH ACTIVITY

Bathing	Cooking	Eating	Going out	Sleeping
4 hours	4 hours	4 hours	—	18 hours

On the other hand, the residents fill in the questionnaire about the mistake and the forgetting of the pressing buttons which the residents recognize. These recognizable defects are added to complement the data stored in the database. Regarding other sensors, there was no defect on the environment sensors, but there were many defects of the door sensors. In addition to the effects of the metal parts of the doors described in the previous section, one of the possible reasons for this is that residents open and close the doors incompletely and quickly. Therefore, we found that it is necessary to select the robust sensor and devise the installation position and method for the long-term operation in general homes.

Resampling of data: In order to analyze data from multiple sensors with different sampling periods, we resample the data to fit time window of 10 seconds. For this, infrared motion sensors and door sensors are resampled as the total number of reactions for 10 seconds, and ambient sensors are upsampled by the previous value. Moreover, the number of seconds elapsed since the start of a day is added to the training data as a new feature value. We expect, by this feature, that recognition accuracy is improved by learning the information of time when various sensors react.

B. Algorithm for Activity Recognition

We use a neural network model with LSTM cells capable of considering time series data as an algorithm for activity recognition. Fig. 4 shows the configuration of the model. The model consists of Input, Dropout, LSTM, Dense and Output layers. We set the number of hidden units of the Dense and LSTM layer to 512, and the dropout ratio to 0.2. The sigmoid function is used as the Activation function of the Dense layer. The number of look-back memory is 100, epoch number is 10, and input batch size is 512.

The ADL data used in this analysis are imbalanced data, because the duration while no activity is performed is longer than the duration of activities performed. In order to construct a learning model considering imbalances, we use weights

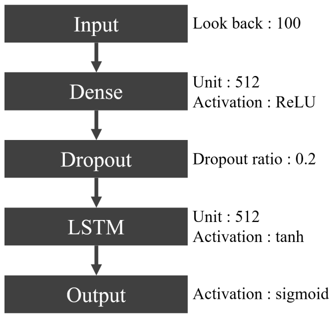

Fig. 4. Overview of neural network model

corresponding to the number of classes for updating cost functions. Specifically, we use the coefficient W_i defined by Eq. 2, where w_i is the weight of each classification class, N is the number of all samples, C_n is the number of classes, and F_i is the number of samples belonging to class i.

$$w_i = \frac{N}{C_n \times F_i} \tag{1}$$

$$W_i = \frac{1 + w_i}{2} \tag{2}$$

As a result, even when an imbalance exists in data, the model can effectively learn from the data, because the optimizer emphasizes a small number of labels.

C. Evaluation Method

We use time-window based cross validation to train and test the model where the data is divided as follows: First, the data segment with the length of look-back (100 samples = 1000 sec) is extracted from the beginning of the time series data. Next, the start point of the extraction in the data is shifted by one sample (10 second) and the data segment with the same length is extracted. This process is repeated until the end of the data. Finally, models (a model for each activity) are trained, validated and tested by using all of the extracted data segments where for each segment the first 80% of the segment is used as training data, the next 10% as the validation data, and the last 10% as the test data.

VI. Result and Discussion

Table III, IV, V, VI and VII show the precision, recall and F score for bathing, cooking, eating, going out and sleeping activities, respectively. In the tables, the results of the proposed method (using W_i as weight), the case using no weight, and using w_i as weight are compared, and they are represented as "proposed," "not weighted" and "w_i," respectively. Fig. 5 shows confusion matrices of the five activities where 1/0 shows if the activity is performed or not. From the tables, we see the following when W_i is used as a weight (proposed method): the highest precision 0.78 is achieved for bathing activity; for cooking and eating, precision is low, but high recall is achieved; and for going out and sleeping activities, high precision and recall are achieved.

On the other hand, when the weight is not used in learning (not weighted), all activities except for sleeping are not well learned (both precision and recall are 0).

When w_i is used as a weight (w_i), lower F score is achieved because a small number of labels are excessively fitted.

Overall, the proposed method with W_i as weight achieved the best recall of 0.824 on average (0.56, 0.77, 0.96, 0.85, 0.98 for bathing, cooking, eating, going out and sleeping, respectively).

Discussion: As the perceived problems, there are missing values of the activity labels of the data collected, and the imbalance of the number of data between the activity labels. The buttons used in the proposed system have a problem that it is difficult to notice the mistake of pressing because the buttons do not give feedback such as beep sound, vibration, lighting, etc. We analyzed the number of mistakes of forgetting to press buttons among activities. As a result, we noticed that the forgetting is less frequent for bathing, going out and sleeping activities which are performed only once in a day, while the forgetting is more frequent in cooking and eating which are performed multiple times a day. Thus, in order to improve the accuracy of activity recognition at general homes, it is essential to collect higher quality data by improving the UI of the data collection system as well as contriving the learning model construction and data preprocessing.

VII. Conclusion

In this paper, we proposed the system consisting of low-cost, easy-to-deploy and low-maintenance cost sensors based on energy harvesting that can collect data of resident's ADLs for months without maintenance. The proposed system was deployed in 10 homes of senior citizens where we collected ADL data for two months each. Then, we estimated the ADLs from the collected data by LSTM, a deep learning model. As a result, we confirmed that the data of the residents' ADL can be collected easily by using the proposed system. Also, we found that the proposed system can estimate ADLs at high recall rate of 82.4% on average. Since recognition accuracy of sleeping and going out are high, it can be applicable to applications including anomaly detection such as nocturia or sleep apnea syndrome, and monitoring services such as wandering detection and alert system in changing behavior.

As future tasks, we are planning to improve the sensor data quality by the qualitative improvement of the sensor installation procedure and the interface of the push buttons. Moreover, we are going to devise an improved version of ADL recognition algorithm which estimates semantic position information of sensors and can learn/apply from/to homes with different floor plans without giving knowledge of the sensor position and/or the layout of rooms.

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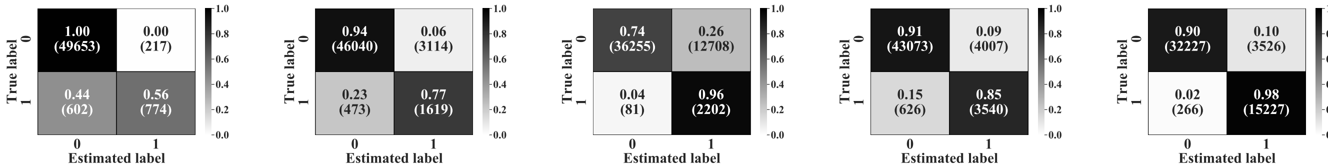

Bathing Cooking Eating Going out Sleeping

Fig. 5. Confusion matrices of five activities

TABLE III
THE RESULT FOR BATHING

	Precision	Recall	F value
Negative_proposed	0.99	1.00	0.99
Positive_proposed	0.78	0.56	0.65
Negative_not_weighted	0.97	1.00	0.99
Positive_not_weighted	0.00	0.00	0.00
Negative_w_i	1.00	0.83	0.91
Positive_w_i	0.14	0.98	0.25

TABLE IV
THE RESULT FOR COOKING

	Precision	Recall	F value
Negative_proposed	0.99	0.94	0.96
Positive_proposed	0.34	0.77	0.47
Negative_not_weighted	0.96	1.00	0.98
Positive_not_weighted	0.00	0.00	0.00
Negative_w_i	1.00	0.51	0.67
Positive_w_i	0.08	0.97	0.14

TABLE V
THE RESULT FOR EATING

	Precision	Recall	F value
Negative_proposed	1.00	0.74	0.85
Positive_proposed	0.15	0.96	0.26
Negative_not_weighted	0.96	1.00	0.98
Positive_not_weighted	0.00	0.00	0.00
Negative_w_i	1.00	0.51	0.67
Positive_w_i	0.08	0.97	0.14

TABLE VI
THE RESULT FOR GOING OUT

	Precision	Recall	F value
Negative_proposed	0.99	0.91	0.95
Positive_proposed	0.47	0.85	0.60
Negative_not_weighted	0.92	1.00	0.96
Positive_not_weighted	0.00	0.00	0.00
Negative_w_i	0.98	0.78	0.87
Positive_w_i	0.26	0.86	0.40

TABLE VII
THE RESULT FOR SLEEPING

	Precision	Recall	F value
Negative_proposed	0.99	0.90	0.94
Positive_proposed	0.81	0.98	0.89
Negative_not_weighted	0.96	0.93	0.95
Positive_not_weighted	0.86	0.92	0.89
Negative_w_i	0.97	0.91	0.94
Positive_w_i	0.82	0.93	0.87

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