

# A Question Selection Method for Active Learning of Context-dependent Motion Labels

Tatsuya Sakato<sup>1</sup> and Tetsunari Inamura<sup>1,2</sup>

**Abstract**—A learning agent cannot determine labels of human motions only with the motions in daily life scenes. The labels of the motions depend on not only the motions but also contexts. However, Learning labels of the motions in all scenes in the real world is impractical for the learning agent. Active learning is proposed as an effective learning method. In daily life scenes, answers of an oracle often include noise. In this paper, we proposed a question selection method for the active learning. Experimental results indicate that the proposed method can reduce noise of the oracle.

## I. INTRODUCTION

A learning agent cannot determine labels of human motions only with the motions in daily life scenes. The labels of the motions depend on not only the motions but also contexts (e.g. used tools, places in which the motions are performed). Therefore, the learning agent should learn context-dependent labels of the motions. However, Learning labels of the motions in all scenes in the real world is impractical for the learning agent. Active learning is proposed as an effective learning method based on statistical criteria[1][2].

In daily life scenes, answers of an oracle often include noise. In this paper, we proposed a question selection method for the active learning. In conventional active learning methods, learning agents select only scenes which are asked to an oracle. On the other hand, in our proposed method, a learning agent selects not only scenes which are asked to an oracle but also questions on the basis of learning progress of the learning agent. We expect that our proposed method progress learning more effective than the conventional active learning method.

## II. PROPOSED METHOD

Figure 1 shows an overview of our proposed method. In conventional active learning methods, learning agents select only scenes which are asked to an oracle. In contrast, in our proposed method, a learning agent selects not only scenes which are asked to an oracle but also questions on the basis of learning progress of the learning agent.

### A. A Question Selection Criteria

In the proposed method, the learning agent asks the oracle a yes/no question of the most probable label in scene  $s$ ,

<sup>1</sup>Tatsuya Sakato and Tetsunari Inamura are with National Institute of Informatics, 2-1-2 Hitotsubashi, Chiyoda-ku, Tokyo, Japan {sakato, inamura}@nii.ac.jp

<sup>2</sup>Tetsunari Inamura is with the Department of Informatics, SOKENDAI (The Graduate University for Advanced Studies), 2-1-2 Hitotsubashi, Chiyoda-ku, Tokyo, Japan

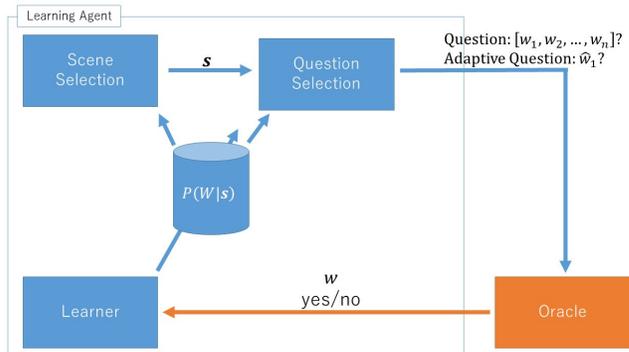


Fig. 1. An overview of the proposed method

which is selected by the same method as conventional active learning methods, if (1) is satisfied in the scene  $s$ .

$$P(\hat{w}_1|s) - P(\hat{w}_2|s) > \theta \quad (1)$$

where  $\hat{w}_i$  is the  $i$ th most probable label in the scene  $s$ .  $\theta$  is a threshold which is a criterion for changing a question type. If (1) is not satisfied in the scene  $s$ , the learning agent asks the oracle a label of the scene by showing all label candidates.

## III. EXPERIMENTAL SETTINGS

In an experiment, the learning agent learns labels of human motions by asking the oracle labels of human motions in each scene. Scene  $s$  is represented as a set of place  $l$ , tool  $t$ , and motion  $m$ .

$$s \in S \quad (2)$$

$$S = \{(l, t, m)\} \quad (3)$$

$$l \in L$$

$$t \in T$$

$$m \in M$$

where  $L$ ,  $T$ , and  $M$  are sets of places, tools, and motions respectively, and  $S$  is a set of scenes. In the experiment, not only the learning agent but also the oracle is a software agent, and is a noisy oracle[3]. The oracle selects correct answer with a probability of 0.8, and the other answer randomly with a probability of 0.2. When the oracle is asked a yes/no question by the learning agent, the oracle answers yes if the asked label is the same as a label selected by the oracle, and no if the asked label is not the same.

In the experiment, threshold  $\theta$  is set to 0.2.

### A. Places, Tools, Motions and Words Used in the Experiment

Places, tools, motions used in the experiment are listed in table I. Labels used in the experiment are listed in table II.

TABLE I  
PLACES, TOOLS, AND WORDS USED IN THE EXPERIMENT

Place	Tool	Word
Beach	(Hands only)	Greeting
Kitchen	Pan	Cooking
Forest	Bat	Cleaning
Game center	Fishing rod	Fishing
	Cloth	Hitting
	Mallet	Cutting
	Ax	Others

TABLE II  
HUMAN MOTIONS PERFORMED IN THE EXPERIMENT

Human motion
Waving a hand vertically (WavingHandV)
Waving a hand horizontally (WavingHandH)
Swinging hands vertically (SwingingV)
Swinging hands horizontally (SwingingH)

### B. Learning of the Learning Agent

In the experiment, the learning agent learns probabilities of that each label corresponds to each scene. A probability of that label  $w$  corresponds to scene  $s$  is defined by

$$P(w|s) = \frac{N_{s,w}}{N_s}. \quad (4)$$

$N_{s,w}$  is a score in scene  $s$ , and  $N_s$  is the sum of  $N_{s,w}$ .

Each  $N_{s,w}$  is set 1 as an initial value. It is added +1 if the oracle answers label  $w$  in scene  $s$ . In addition, it is added -1 if the oracle answers yes for yes/no question of label  $w$ . It remains its value in the other case.

$N_s$  is defined by

$$N_s = \sum_w N_{s,w}. \quad (5)$$

### C. Scene Selection Policies

Scenes asked to the oracle are selected on the basis of a scene selection policy. Scene selection policies used in the experiment are listed in table III.

TABLE III  
SCENE SELECTION POLICIES USED IN THE EXPERIMENT

Scene selection policy
Random selection (random)
Entropy-based (entropy)
Margin sampling (margin)
Least confident (l.conf.)

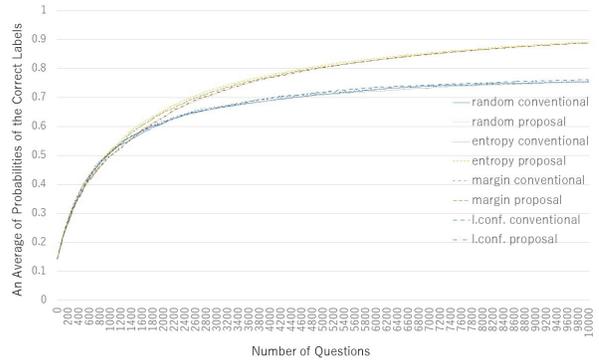


Fig. 2. Changes of an average of probabilities of the correct labels in all scenes

TABLE IV  
AN AVERAGE OF PROBABILITIES OF THE CORRECT LABELS IN ALL SCENES LEARNED BY THE LEARNING AGENT IN EACH METHOD

	random	entropy	margin	l.conf.
conventional	0.75	0.75	0.76	0.76
proposal	0.89	0.89	0.89	0.89

## IV. RESULTS AND DISCUSSION

Figure 2 shows changes of an average of probabilities of the correct labels in all scenes. Table IV shows an average of probabilities of the correct labels in all scenes learned by the learning agent in each method. In the experiment, the oracle answers correct labels with a probability of 0.8. The expected acquired probabilities of the conventional methods did not exceed this probability. However, the proposed methods using each scene selection method exceeded this probability. We expect that the proposed method could reduce noise of answers of the oracle.

## V. CONCLUSION

In this paper, we proposed a question selection method for active learning of context-dependent motion labels. Experimental results indicate that the proposed method can reduce noise of the oracle.

In the experiment, the proposed method selects meaningless scene (e.g. swinging vertically motion with a bat in a kitchen). Reducing selecting such kind of scenes is one of the aim of the next step of our research.

## ACKNOWLEDGMENT

This work was supported by JSPS KAKENHI Grant Number JP17K18331.

## REFERENCES

- [1] B. Settles: “Active learning literature survey”, Computer Science Technical Report, no.1648, 2009.
- [2] Tatsuya Sakato, Tetsunari Inamura: “Interactive Learning of Context-dependent Relationship between Human Motions and Words”, The 31st Annual Conference of the Japanese Society for Artificial Intelligence, 4D1-OS-37c-5, 2017.
- [3] P. Donmez, J. Carbonell, J. Schneider: “Efficiently Learning the Accuracy of Labeling Sources for Selective Sampling”, In Proc. the International Conference on Knowledge Discovery and Data Mining, pp. 259–268, 2009.