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A Point-Pass-Based Action Prediction Method

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***Abstract*— This paper describes a basic idea how to realize an intelligent learning room system. Such a system needs to have dynamical adaptive capability for each user. We have proposed a method to predict user action using Inductive Learning with N-gram. The system based on our proposed method is able to acquire rules automatically from data pairs through Inductive Learning. As unified with N-gram, the system demonstrates a high predictive accuracy. However,the acquired rules express the user's habits and preferences. Consequently, it is possible that the system adapts dynamically to each user. The user need to proofread the errors in prediction results. Therefore the prediction ability improves. As a result, the number of errors decreases. This paper unifies N-gram and Inductive Learning to develop the Point-Pass-Based Prediction system. The system was found to have good accuracy of which the highest prediction accuracy was about 89.3(%). The system was improved that it has high dynamic adaptive ability.**

I. Introduction

With the global spread of information technology, the need has arisen for an intelligent learning system. To realize intelligent learning system, it depends on the mechanism of machine learning.

In machine learning researches, the important field is to give users the means to perceive and manipulate easily huge quantities of information under resource constraints. If future intention or action of a user can be correctly predicted, it means that the system can give the user much convenience. Such systems need to have high prediction accuracy, high dynamic adaptation capability and high flexibility.

To realize this Intelligent system, one of the most important problems is how to predict user actions. It is clear that each user behaves differently, and it is difficult to give prepared knowledge for the system because it needs huge labor if we try to prepare these knowledge for each user.

A possible solution to this problem is to use the Rule-based Machine Learning method[1] as analytical approach, furnish the system with rules in advance. However, since habits and preferences vary from one user to another to prepare these rules requires huge labor, it is impossible to prepare rule dictionary in order to deal with each user.

On the other hand, the most conventional action prediction technique takes the statistical approach. According to the method of data analysis, the statistical approach is classified into Point-Based Prediction[2,3,4] , and Pass-Based Prediction[5,6]. Almost all Point-Based Prediction systems use the Markov model or the Expectation Maximization Algorithm. Achieving high accuracy with a exclusively statistical approach requires substantial amounts of data. As a result, many researchers have proposed methods that use N-gram to analyze time-series data as the Pass-Based Prediction System. However, the prediction accuracy depends on the amounts of the input data. Prediction becomes impossible when the predicted target appearance frequency is low. It is the situation known as the "data sparseness problem".

To resolve these problems of user action prediction system, one idea is adopting the natural language processing techniques into the action prediction system. On the machine translation techniques, the Example-based and the Statistical machine translation[7] have been proposed to resolve the Rule-based problems. Systems based on these methods are able to increase its correct translation rate as learning data increases. These systems need large data for the high quality translation. It is difficult that the system enables prediction for each user's action because it is not easy to collect sufficient data for each user. As a result, it is not enough to adopt Example-based method to our system.

K.Araki et al. have proposed Inductive Learning of Natural Language Processing approaches. Using Inductive Learning, inherent rules are acquired through recursive extraction of the overlapping and different parts from input data pairs[8]. The effectiveness of this method has already been proven in natural language processing[9,10,11,12]. The acquired rules express the user habits and preferences, consequently, the system adapts dynamically to each user.

The action prediction system based on this method is able to acquire the rules from the single appearance of performed action on data by Inductive Learning automatically. For increasing the correct prediction rate, we adopt the N-gram into our system, too.

It is clear that a person action has two characteristics: (1) their uniqueness for the particular environment or situation, and (2) their consistency of regular habits over a long period. We can use causality to determine the rules form, and the acquired rules in Inductive Learning express the uniqueness

TABLE I
EXAMPLE OF INDUCTIVE LEARNING

Input1	$\alpha\theta\sigma$ $\underline{\phi\delta}$ $\lambda\upsilon$	
Input2	$\Xi\Sigma$ $\underline{\phi\delta}$ $\Phi\Theta$	
Segment1	$\alpha\theta\sigma$	$\Xi\Sigma$
Segment2	$\underline{\phi\delta}$	$\underline{\phi\delta}$
Segment3	$\lambda\upsilon$	$\Phi\Theta$

TABLE II
EXAMPLE OF RECURSIVELY EXTRACTION

Segment1	α $\underline{\theta\sigma}$	γ $\underline{\Phi\Theta}$
Segment2	$\underline{\theta\sigma}$ $\gamma\mu$	$\underline{\Phi\Theta}$ Σ
Primitive1	α	γ
Primitive2	$\underline{\theta\sigma}$	$\underline{\Phi\Theta}$
Primitive3	$\gamma\mu$	Σ

of the user's action.

In this paper, we use Inductive Learning to acquire action sequences as scripts. The scripts express user performed tasks. The consistency of actions (scripts) can be analyzed using N-gram. The acquired rules can be optimized from the unified information. The system automatically chooses the most suitable rule using a reasonable credibility evaluation function, and generates a data history and a rule dictionary.

We define our method as a Point-Pass-Based action prediction method using Inductive Learning with N-gram (N-IL-PS).

Accordingly, it is reasonable to use Inductive Learning[8] to acquire rules to predict user actions from given data. Our method predicts user action through Inductive Learning with N-gram, i.e., a prediction system that adapts dynamically to each user.

In this paper, we outline this system and examine the experimental results to evaluate the system's adaptability. We then indicate potential directions of future research.

II. INDUCTIVE LEARNING WITH N-GRAM

This paper addresses a Point-Pass-Based action prediction method. The Inductive Learning is a Point-Point-Based method and n-gram is a line-based method for machine learning. We unify these two learning algorithms to achieve the adaptive capbility as a complex and dynamic prediction system.

The action prediction research is very important in Machine Learning researches. There are many prediction systems in other environments, such as Unix commands predicting[13], user action sequences predicting[14] and future user actions predicting[15]. In these systems, neither the prediction accuracy nor the dynamic adaptive capbility are satisfiable.

Our mothed differs these prediction systems, do not fall into the mothed of traditional statistical time-series analysis techniques and the analytical approaches.

Here we introduce the basic idea of Inductive Learning[8]. Table 1 shows an example of extraction of correspondences from unknown character strings prepared by human being.

According to this heuristics, we can extract different parts and common parts as segments from data pairs. Moreover primitives can be extracted from the segments with this idea too. Table 2 shows an example of the primitives extracted from segments. The idea of Inductive Learning is to automatically acquire knowledge in multistage steps by extracting common parts and different parts. The learning process of our system is based on these processes as mentioned above.

In natural language process, N-gram or collocation plays a significant role in computational linguistics. A collocation is a "recurrent combination of words that co-occur more often than expected by chance and that correspond to arbitrary word usages" and they typically are found by computing the probability of bigram and trigram. N-gram is also usually using for the action prediction system. In this paper, we unifiy the Inductive Learning and N-gram as a Point-Pass-Based prediction method.

TABLE III
ELEMENT'S FIXED VALUE

ELEMENT	SETTING VALUE
Day of week	Monday,Tuesday,...,Sunday
Time	hh,mm
Brightness	50Lux,100Lux,...,1450Lux,1500Lux
Temperature	$16C^{\circ}$,$17C^{\circ}$,...,$34C^{\circ}$,$35C^{\circ}$
Door	Doof,Don
TV	Toff,1ch,2ch,...,59ch,60ch
TV-program	None,Sport,News,...,Film,Music
Curtain	Coff,Con
Light	Loff,Lon
Air conditioner	Aoff,$16C^{\circ}$,$17C^{\circ}$,...,$34C^{\circ}$,$35C^{\circ}$
Telephone	Teloff,Ring,Telon
Alarm clock	Boff,Bon

III. SYSTEM DESIGN AND FUNDAMENTAL CONCEPT

Here we explore the heuristics for developing a general-purpose action prediction system which can adapt dynamically to each user. To this end, we provide a hypothetical version of our system, a "Learning Room", and investigate the engineering principles behind it.

The prediction problem is difficult for a "Learning Room" where there are multiple inhabitants performing multiple prediction at the same or different times. As a first step, we investigate a portion of this problem: predicting a single user's actions and intentions.

To simplify analysis, the Learning-Room consists of eight artificial elements, door(D), television(TV), TV program(P), curtain(C), electric light(L), air-conditioner(AC), telephone(TEL) and alarm clock(AL), and four natural elements, Time, brightness(B), and temperature(T) and day of week(W). All elements are shown in Table 3. An artificial element is one whose state can be changed by the user, while a natural element, such as time, temperature, or brightness, does not depend on user actions. Each element receives an initial state value. Here we assume that all of the states can be acquired automatically by the system.

TABLE IV
DYNAMIC TABLE FOR PREDICTION

$...rule^{n-2}rule^{n-1}rule^{n}$	IL credibility of $rule^{n}$	N-gram information	unified information of IL and N-gram

The user actions need to be accessible in some tangible form, and then we can generate a sequence of historic actions as a string of action symbols or we can represent individual actions as separate states with corresponding state transitions.

$$S^n_k = (N^n_k, A^n_k)^1 \quad (1)$$

(N^n_k) expresses natural elements vector space, and (A^n_k) means artificial element vector space as follows:

$$N^n_k = (W^n_k, Time^n_k, B^n_k, T^n_k) \quad (2)$$

$$A^n_k = (D^n_k, TV^n_k, P^n_k, C^n_k, L^n_k, AC^n_k, TEL^n_k, Al^n_k) \quad (3)$$

IV. USE OF INDUCTIVE LEARNING WITH N-GRAM

According to the basic idea of Inductive Learning, by extracting the different part from artificial elements states, we can acquire initial rules as follows:

$$Rule^n_k = (S^n_k, Action^n_k) \quad (4)$$

, where, ($Action^n_k$) expresses the actions performed by user. For examples are shown as Figure 1:

データの例1(順番で S^1_1, S^2_1, S^3_1):
(Monday,7:31,750,24,Doff,3ch,News,Con,Loff,Aoff,**Ring**,Aloff)
(Monday,7:31,750,24,Doff,**3ch,News**,Con,Loff,Aoff,**Teon**,Aloff)
(Monday,7:31,750,24,Doff,**TVoff,None**,Con,Loff,Aoff,Teon,Aloff)
データの例2(順番で S^1_2, S^2_2, S^3_2):
(Tuesday,10:03,800,28,Doff,1ch,News,Con,Loff,Aoff,**Ring,**Aloff)
(Tuesday, 10:03,800,28,Doff,**1ch,News**,Con,Loff,Aoff,**Teon**,Aloff)
(Tuesday, 10:03,800,28,Doff,**TVoff,None**,Con,Loff,Aoff,Teon,Aloff)

Fig. 1. Examples of data

Then we can acquire two initial rules, such as:
$Rule^1_1 = (S^1_1, \mathbf{Telon})$
$Rule^2_1 = (S^2_1, \mathbf{Toff}\&\mathbf{None})$

In order to acquire rule adaptation capability, we perforn abstraction process for initial rules using IL. The abstractioı process algorithm is shown as Figure 2.

Using Inductive Learning, we can extract user action se quence as a script. For example, from the example of data se 1, we can extract this script: $(Head \rightarrow Ring : S^1_1 \rightarrow Teon$ $S^2_1 \rightarrow TVoff|None : S^3_1 \rightarrow Tail)^2$. In this paper , we us trigram to analyze action's conditional probability.

A script is a memory structure that expresses the standard ized action that a person performs consistently over time[16 . These scripts are different with each user being everyon has many scripts. When facing a specific situation, a person chooses and performs a suitable script based on the predicted result.

For prediction process, we unified IL and N-gram with a dynamic table, as shown in Table 4.

V. OUTLINE

This section describes the procedure of our proposed method. As shown in Figure 3, our system procedure consists of prediction process, proofreading process, feedback process and learning process.

In prediction process, as we give certain amount of dataset to the system, it makes prediction by pattern matching, while referring to the data history and the rule dictionary. With reference to the rule dictionary, the highest credibility evaluated rule is selected by the system. With reference to the data history, the room state is acquired in accordance with the user action.

In proofreading process, when the predicted result matches the user's action, the state will be registered into the state history. Otherwise, the user performs proofreading, i.e., the user judges whether the action is correct or not. If not, the corrected result will be registered into the proofreading history, and then feedback process takes place.

In feedback process, rules credibility is updated based on four values tracked each rules those values are correct prediction frequency (CF), error prediction frequency (EF), correct prediction rate (CR) and error prediction rate (ER). The system automatically determines the superior of several competing rules. Rules are classified into four ranks, which are Most (M), Higher (H), Common(C), and least (L), and rules are applied in this order of ranks; Table 5 shows the dictionary ranks.

```
Algorithm:abstraction process (A: user's current action;
        m: element's total number;D: rule dictionary)
Begin
Filter D then extract all acquired initial rules of current action A into the TempActionArray.
Initialize the array AbstRuleArray that stores results of acquired abstracted rules.
    If TempActionArray < 1
        return ("No abstraction rule")
    Else
        Begin
          While(TempActionArray)
            RuleA = shift TempActionArray
            Foreach(TempActionArray)
                For j = 1 to m
                    Comparing each attribute's value with RuleA.
                    To extract the common and different parts.
                    Update AbstRuleArray
                End For
                Last if TempActionArray < 1
            End Foreach
        End While
        Return AbstRuleArray
      End
    End If
End
```

Fig. 2. Abstraction process algorithm

[1]"n" is the number of given data, "k" express the date of given date
[2]Telphone Rings, take it to speak something(Teon), turn off the television and no TV program(None)

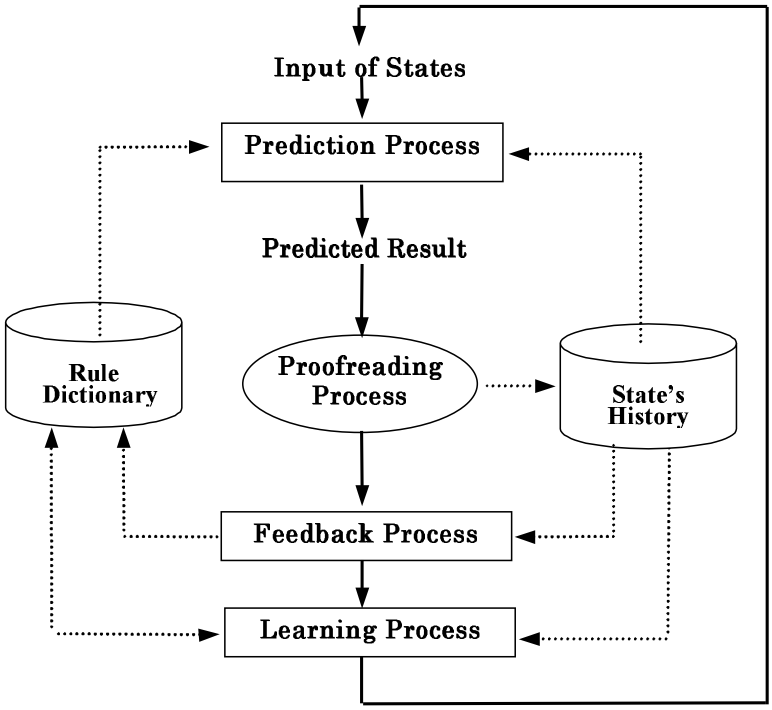

Fig. 3. Outline of the Procedure

TABLE V
CLASSIFIED RANK OF RULE

Name of Rank	Correct Prediction Rate(%)
$Most(M)$	$CR \geq 90$
$High(H)$	$70 \leq CR < 90$
$Common(C)$	$30 \leq CR < 70$
$Least(L)$	$CR < 30$

The rule rankings are updated simultaneously with CF, EF, CR, and ER. The credibility evaluation function (CEF) of our proposed method is defined as follows:

$$CEF = CR - \alpha * ER + \beta * P(A_n|A_{n-2}A_{n-1}) \quad (5)$$

,where: α and β are coefficients.

$P(A_n|A_{n-2}A_{n-1})$ is the analyzed result that expresses the conditional contiguity action probability based on trigram.

The correct prediction rate(CR) and the error prediction rate(ER) are defined as formula (2) and (3):

$$CR = \frac{CF}{CF + EF} * 100(\%) \quad (6)$$

$$ER = \frac{EF}{CF + EF} * 100(\%) \quad (7)$$

The learning process consists of the following steps: acquisition of initial rules, rule abstraction process, acquisition of action scripts, analysis of $P(A_n|A_{n-1}A_{n-2})$ with trigram, and rule information updating. This implementation provides the possibility that the system is able to adapt dynamically to each user. When performing rule abstraction process, in order to decide the criteria of common parts for natural element states. We gave some range for each natural element. Time is 10 minutes, brightness is 50 Lux, and temperature is $2°C$.

The rule adaptive ability improves according to the number of iterations of the abstraction performed. If the abstracted rule is repeated excessively, the prediction accuracy will go down. For this reason, our system needs the suitable degree of abstraction. Since artificial elements and natural elements have unique aspects, we defined two degrees of abstraction. which are shown in the formula (8) and (9).

$$Dan = \frac{X}{N} * 100(\%) \quad (8)$$

$$Daa = \frac{Y}{M} * 100(\%) \quad (9)$$

,where: *Dan* is the degree of abstraction for the natural elements in the rules. *X* is the number of variables in the natural elements portion. *N* is the number of natural elements. *Daa* is the degree of abstraction for the artificial elements in the rules. *Y* is the number of variables in the artificial elements portion. *M* is the number of artificial elements.

VI. EVALUATION EXPERIMENT

As mentioned above, the system based on the procedure shown in Figure 3 was developed for experimentation to investigate the validity of our proposed method. It is differs with the conventional statistical experimental method that our method does not need training data. We used open data for our evaluation experiments, a decision which means that we did not use the same data in the repeated learning. The daily input data for our system was used as learning data, and we

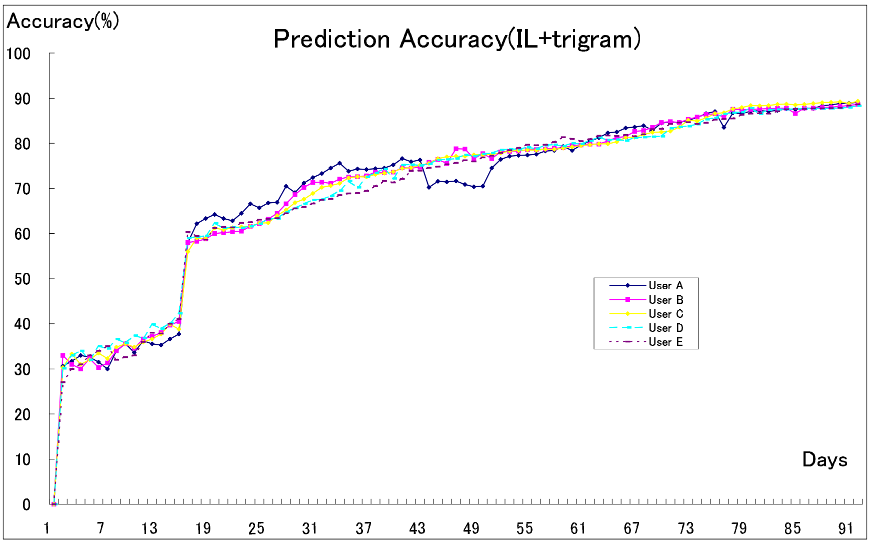

Fig. 4. Transition of Prediction Accuracy of IL+trigram

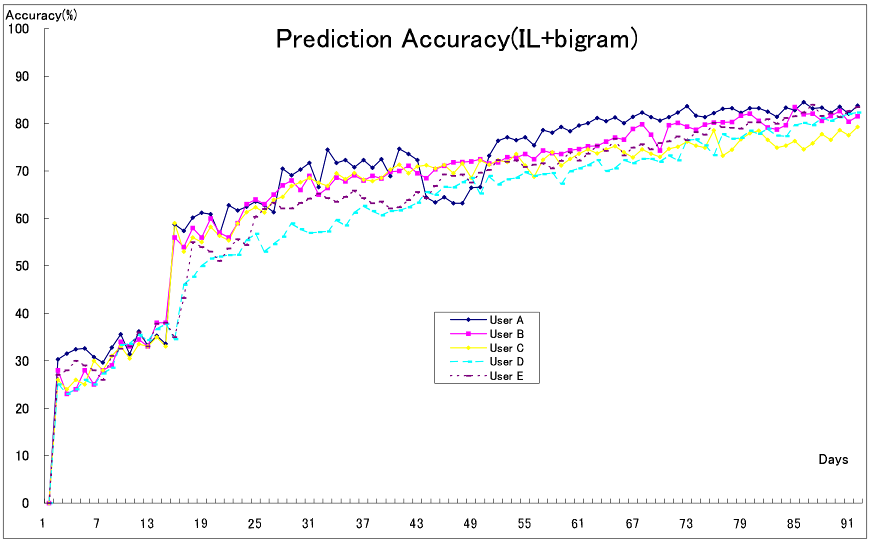

Fig. 5. Transition of Prediction Accuracy of IL+bigram

simultaneously evaluated the system's performance against the predicted result.

In the most of machine learning experiments, cross-validation is the standard method of evaluating the performance of an algorithm with a single dataset of independent examples. If cross-validation is inappropriate, partitioning the data into separate training and test sets is usual.

However since our aim is to propose an adaptive approach, we will evaluate online performance. It means our algorithm is tested on the current action using preceding actions for training. Therefore, we do not perform cross-validation evaluation. We divided data into training and testing data. According to the procedure of Figure 3, after the learning process, the proofreading and the feedback process, test data becomes a new entry in training data, which means every new entry enlarges usable training data in our online system.

The data was collected based on the person actual life, from five graduate students of graduate school of engineering, We generated about 16,000 data that corresponded to a period of 91 days.

Since our aim is to develop a dynamic adaptive prediction system for each user, in order to keep the starting state constant for each user, the data history and the rule dictionary always started from empty initial state.

We define the Correct Prediction Rate (CPR) as follows (10).

$$CPR = \frac{P_+}{P_+ + P_-} * 100(\%) \tag{10}$$

,where: P_+ is the number of correct prediction results. P_- is the number of incorrect prediction results.

The correct prediction result is judged by user according to next input data in the data history. However, a user in the real world does not necessarily choose actions in the same way that this evaluation method does. The user's reaction determines whether the correct result will be selected when plural prediction results appear. Clearly, there is some evaluator subjectivity in real-world situations.

In order to optimize the coefficients of the credibility evaluation function, we did some preliminary experiments. We applied the Greedy Method [17] to all collected data to obtain the optimal coefficients for the credibility evaluation functions. In the formula (5) the parameters were found to be 10 and 50 respectively. For the abstracted rules, both the values of Dan and Daa are 0.5 by preliminary experiments.

VII. Results and Discussion

In this section we describe our experiments. In Figure 4 we plot the performance of our proposed method. We just use the top prediction result to evaluate the accuracy of our experiment. It is shown that our method had good prediction performance.

We found that the highest prediction accuracies for users are about 89.1% (A), 88.6% (B), 89.3% (C), 88.3% (D), and 88.7% (E). It means that the system based on our proposed method is able to acquire many immanent causality rules automatically from data pairs through IL. Being unified with N-gram, the information of user-performed actions can be enough for prediction.

This level of predictive accuracy obviates the need of preparing data history and rule dictionary in advance. The acquired rules express the user habits and preferences. Therefore, the system can adapt itself dynamically to each user. The user needs to proofread the errors in prediction results, hence the prediction ability improves. As a result of the system dynamic adaptation, the number of errors decreases.

We also did some experiments of IL with bigram. Figure 5 shows the prediction accuracy of IL with bigram. With these results, We can draw two conclusions from the comparisons:

(1) Both two systems can acquire good prediction accuracy and high adaptation capability.

(2) IL with trigram system demonstrates higher accuracy than IL with bigram system, being the causal relationship rule can be extracted from the user performed action scripts.

(3) Our method does not need large database in advance.

(4) The Point-Pass-based prediction method validity was proved.

VIII. Conclusions and Future Work

In this paper we have described our approach to predicting a user actions in an intelligent system such as a learning room. Our method differs from conventional statistical and analytical approaches. It is showed that our system performance has good accuracy for each user. Furthermore, we also observed that our system could adapt dynamically to any user, since the data history and the rule dictionary were always initially empty. We did not need to prepare data history and rule dictionary beforehand. We defined our proposed method as a Point-Pass-based Prediction System with the unification of IL and N-gram.

In our future works, we hope to certify the validity of adaptation to a variety of users, to prove the flexibility of the system with multiple users, and to use the HMM Model to increase the prediction accuracy.

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