A SOFTWARE SYSTEM EVOLUTION IN HUMAN-CENTRIC ENVIRONMENT DRIVEN BY NEW USER INTENTION DETECTION USING CRF

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Abstract - The Software Service Evolution can easily determine through requests for changes, improvement,andenablement of knowledge development continuously from users', as compared tothe other factors. It is unavoidable for almost all software andcan be seen as the development of system-user interactions. The ability to precisely and effectively monitor users' volatile requirements is perilous that requires to make a timely improved system for adaptation of fast varying environments. In this research,a methodologyappliesConditional Random Fields (CRF) as a mathematical foundation to discover the users' potential desires and requirements in order to delivera quantitative exploration of system-user interactions. By examiningusers' run-time behavioral patterns, domain knowledge experts can predict how users' intentions shift. The results also show the effects of different regularization algorithms of CRF on the training model. Our supremeobjective is to acceleratesoftware service evolution by using machine learning techniques. To detect users' intentions using the CRF method, an experiment on an open-source software is performed.

Keywords - Conditional Random Fields, intention, requirement, software service evolution, target.

I. INTRODUCTION

The adaptation to ever-changing user requirements and the operating system is the main goal for the evolution of a software system [1]. Currently, most of the software systems required evolution that is considered an essential quality [2], [3] since the nature of human demands are ever changing and abrupt evolving [4] and real-world systems have volatile environmental changes [5].The advancement of system-user interactions can be viewed from the evolution of software services.The ability to precisely and effectively monitor users' volatile requirements is perilous that requires to make a timely improved system to adapt rapidly changing environments. Conventionally, manual analysis and based on business needs or delayed user feedbacks were used to elicit these new requirements [6], which made the base to continue the software evolution nowadays.

The inference process of Situ [7] framework is proposed that allows to make model and detect human intentions by taking the targets of an individual, including catching the behaviors through observations. An interpretation procedure based on the Hidden Markov Model (HMM) considerably reduce service evolution cycle and creates instant individualized services definition at runtime possible. Situ [7] recommends that A human perceived situations according to its internal mental condition (target), i.e., actions, and the target achieved can be easily interpreted as exterior reflections. The externally observable of human behaviors are represented by some context value changes. If the user has a new approach for achieving a predetermined target or the user has a new target, both will result in a new intention detection. As these two cases reveal a user's new requirements,therefore, they are beneficial for the improvement of the system.

Conditional Random Fields (CRF) is a statistical modeling method which is used in our research thatdetects users' targets by providing a quantifiablestudy of interactions between system and user. By examining users' run-time behavioral patterns, knowledge-baseddomain experts can have a great idea aboutchanging in users' intentions. CRF model is constructed through the training data acquired by an experimentation on anopen-source software wasperformed and the method of new user intention detection is demonstrated.CRF-L1 and L2 are regularizations to reduce the overfitting and improve the classification accuracy of model construction. Margin Infused Relaxed Algorithm (MIRA) is another algorithm to train the CRFs. An experimental comparison is also explained among regularizations algorithms to get the maximum accuracy that helps to provide accurate inference probability.

II. RELATED WORK

2.1. System Evolution and Requirements Elicitation

The software system grows continuously, as it increases the complexity of the system will also increase and will require more efficient methods. To make sure the flexibility and reliability, the target of software evolution is to perform significant

modifications to the system. In general, software evolution defines as the study and management of the process of performing significant modifications to software in a timely manner.

Throughout the whole system lifetime, the change identification continues and suggestions for change are the drivers of system evolution. A cooperative learning process of requirements engineer with the customer can be reflected in the traditional requirements elicitation procedure [8], as this procedure mainly depends on requirements engineer for performing the subjective analysis and prediction, it is typically inefficient and results in erroneous requirements. A cycle of modification, elicitation, development,and deployment takes too much time to finish. In order to turn timely and critical service individualization into reality, the researchers are facing many challenges to overcome unpleasantly long evolution cycles nowadays. New technologies should be introduced for fast growing software evolution.

2.2. The inference process of Situ Framework

The inference process ofSitu [7] is proposed to detect humanintention in context-aware service environments. It infers human target since most are hidden and capturessubsequent context values by observing that provides people to detect human intentions and model. While detecting intention along with prediction mechanism, Hidden Markov Model (HMM), Situ is intended to build the instantaneous description of individualized services at runtime possible and greatly reduce service evolution cycle.

Situ describesa situation that includes the users' target as a time-stamped status together with users' behaviors (context value & action). Formally, the situation is expressed by 3-tuple {t, A, E) at time t, where t is a set of atomic target, A is set an of behavioral context and E is a set of environmental context. And intentionIis represented as I = seq (S_1, S_2, ...,S_k), where S_1, S_2, ...,$S_k$are temporal sequence of situations threaded through an atomic target t.

2.3. CRF (Conditional Random Fields)

CRF is a mathematical foundation that provides a method used to encode well-known relationships between observations and build reliable interpretations [9].CRF is mostly used for parsing or labeling the sequential data. A CRF model should be built that can encode users' standard behavior pattern so that it identifies new intention with low confidence is indicates users' divergent behaviors. The standard CRF model is developed from the training data that are collected by observing user behaviors who are expected to correspond to the system design. The CRF model will be used in the result of target inference to label with targets the divergent behaviors in low confidence, and in order to elicit user's potentially new intentions they can be easily singled out and examined. Apart from the divergent behaviors, new requirement or system drawbacks will also be detected by analyzing users'target transitions and erroneous behaviors.

To acquire the effective labeling for an observation sequence S, the CRF model marks every possible target-sequence T by summing the weighted feature functions f_j over all data in the sequence:

$$\text{value}(T \mid S) = \sum_{j=1}^{u} \sum_{i=1}^{v} \omega_j f_j(S, i, T_i, T_{i-1})$$

Where ω_j is the weight correlated with feature function f_j. The target-sequence T with the largest value (T | S) will be chosen as the labeling for the observation sequence S. The Viterbi Algorithm [10] is employed in value (T | S) for minimizing the computation complexity and Limited-memory BFGS algorithm is used for calculating the weights ω_j of feature functions f_j. To maximize the accuracy of inference results we did experiment on different CRF regularizations. Regularization is a machine learning technique to reduce learning model overfitting. Results shows in section 4.4.

CRF regularizations and MIRA algorithm are:

1. L2 regularization

It is also known as Ridge Regression.

$$\max_w L(Y|X; w) - \lambda w^T w$$

The parameter λ controls the degree of smoothing. Higher the smoothing, λ will be high value.

2. L1 regularization

It is also known as Lasso Regression.

$$\max_w L(Y|X; w) - \lambda \sum_i |w_i|,$$

Again λ controls the degree of smoothing. Regularization with L1 make training model complex.

3. MIRA

Margin Infused Relaxed Algorithmis an online learning algorithm developed by Crammer and Singer (2003).In each round during training, the model algorithm updates the weight vector. MIRA processes one data set at a time in compared to others offline algorithms of CRFs.

III. NEW INTENTION DETECTION

3.1. Basic Concepts

The CRF model involvesvarious feature function and each feature function specify the relations between target and observations. some basic idea used in the CRF model is described as follows:

Action: It is the user's operations on the system interface.

Context: An entity in the system domain that can be used to describe the status of any information.

Observed-status: A set of observations (action & context values) that are captured at a specific time.

Intention: an execution path for accomplishing specific target.

Situation: A situation thatdescribes a time-stamped, including the user'sbehaviors (actions, context value),andtargets.
Target: the status or goal that user wants to accomplish.

3.2. Target Inference and New Intention Detection

As the prerequisite for detecting new intention, target inference is to infer users' target for each observation at a specific time point. To work out on this, an inference model should be built by encoding the interactions between targets and observations (actions & context values). We build inference model by using CRF in this research article. Target inference and new intention detection can be defined as follows:
Target Inference: Inference model acquires input asequence of observations and gives users' target for each observation at a specific time point as an output in target inference.
New intention detection: In new intention detection users' new behavior sequence pattern accomplishing a target, which is not predefined in the knowledge base domain.
We detect new intention using the following three methods in this research article:
a) Method I: Comparison of divergent with identified behaviors;
This method belongs to detecting users' divergent behaviors by comparing it with the identified behavior patterns.
b) Method II: Obtaining a new intention;
In this method, a new intention based on target evolutions is obtained and it can be assumed to make the target changeovers more efficiently and competently when two targets appear successively.
c) Method III: Get erroneous behaviors;
New targets from users' erroneous behaviors are found when users have newtargets i.e. problem in uploading a file and system didn't mention the maximum and minimum size.

3.3. New Intention Detection using CRF

The mathematical method Conditional Random Field (CRF) is used in this paper to build the model for new intention detection and target inference. A linear chain CRF method is used. The CRF model acquires input asa sequence of observations and gives users' target inference with the highest confidence.
To find the output target inference in method 1 which indicate the detail process of users' low confidences is as follows:

1) Stage 1: Create a CRF model. The CRF model is built based on the training data which acquired through the users' observed-status.
2) Stage 2: After building the CRF model, record user's behaviors (actions & context values).
3) Stage 3: Inference probability is calculated from the CRF model of each output inference targets.
4) Stage 4: By Finding the output targets with low confidence, examine the corresponding users' divergent behaviors.

3.4. System Evolution process

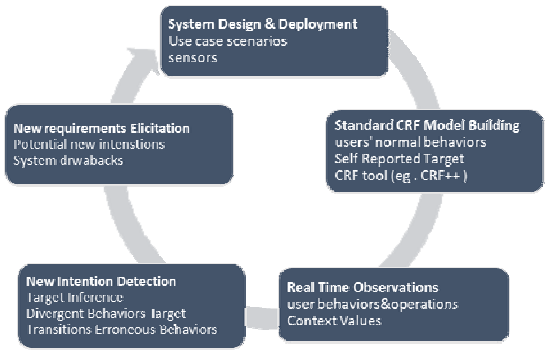


Figure 1. System Evolution Process Using CRF.

System drawbacks are eliminated by system engineers who differentiate between the new intentions and detected potentially system drawback that is mentioned in step 1 of flow chat. This step is purely performed by a domain expert, the system can't perform automatically.Identifying the system drawbacks is not a tough task but new intentions are implied and ambiguous.
Knowledge-based domain experts have two options, first is to directly ask the users if possible and other is to estimates the new intentionsand then verify them. The system can be redesigned based on users' new intention satisfaction or by providing a solution to the disclosed problems. Figure.1 shows the system evolution process on user new intention using a CRF. The complete system evolution process to detect new intentions by applying the CRF model is shown in Figure 1.

IV. EXPERIMENTATION ON A SYSTEM

4.1. Platform using for Experiment
To detect the new intentions using CRF method andto improve system evolution, an experiment is conducted on anopen-source software.We took an online system to shareviews on research papers. To monitor users' behaviors an embedded program is deployed in software as an agent to record data.Users can submit papers/comments on papers, view/download papers and filter the papers.User's actions, as well asthe contents on the selected web pages, will be stored in the database.

4.2. Process for Experiment

Users' actions,context values,andtargets are recorded as raw data. The experiment is run in two rounds to demonstrate the evolution process. The procedure for the experiment shown below:
1) Firstly, Install the Systemversion 1;
2) Run experiment of thefirst-round: callusers togather data of users' actions,

targets,andcontext-values, after that evaluate the predicted users' new intentions;

3) Based on the predicted new users' requirements to revise the system and deploy version 2;
4) Run experiment of the second-round: call users again to gather data of users' actions, targets,andcontext-values, evaluate users' new requirements and estimate the system enhancement.

4.3. Data using for Experiment

Around 7,000 data records and 300 sessions taken from the raw data record, after cleaning the raw data that contains the users' actions, context-values, and self-reported targets at a specific time. A training data which is processed has the following format:

Table1.Training data segment

Observed-status	Time	Target
clickMenuMyProfile	20s	ViewProfile
clickLogin&LoginGood	5s	ViewProfile
clickMenuMyProfile	60s	ViewProfile
clickCancelMyProfile	60s	ViewAPaperInfo
clickMenuAllPapers	10s	ViewAPaperInfo

Observed-status, time-interval,andtargetare three elements of data record:
Observed-status: the format of observed-status is action&context-values;
Time-interval: it is the time between two followingobserved-status. Intervals5, 10, 20, 30, 60(seconds),(m)minutes and (h)hours that used from raw data to processed data;
Target:goals that reported by participants.

4.4. Creating the CRF Model

To detect users' divergent behaviors a CRF model is created and used.Around 5,000 data records are used as the first-round experiment. A standard CRF model iscreated on the training data records using CRF++. To build the standard CRF model feature template is required to define the specific formats of training data as shown in Table 2.

Table 1. Unigram and Bigram Feature templates.

Unigramfeatures	Bigram features
U01:%x [0,0] U02:%x [−1,0]/%x [0,0] U03:%x [0,0] / %x [1,0] U04:%x [−2,0]/%x[−1,0]/%x [0,0] U05:%x [−1,0]/%x[0,0]/%x[1,0] U06:%x [0,0]/%x[1,0]/%x[2,0]	B01:%x [0,1] B02:%x [0,0]/%x [0,1] B03:%x [−1,0]/%x[0,1] B04:%x [−1,0]/%x [0,0] /%x [0,1]

In this paper, it is also observed that the CRF algorithm with L2regularization gives the highest accuracy in compared with L1 regularization andMIRA (Margin Infused Relaxed Algorithm) as shown in Figure 2. L1 and L2regularizations are two related techniques used for reducing the training model overfitting. The term smoothing is also used for regularization. Single-best MIRA is an online-learning algorithm, makes a prediction on the training data that gathered from the model. 93.40% accuracy results from L2regularization helps in our experiment,that is used to create a CRF model for better inference probability output.

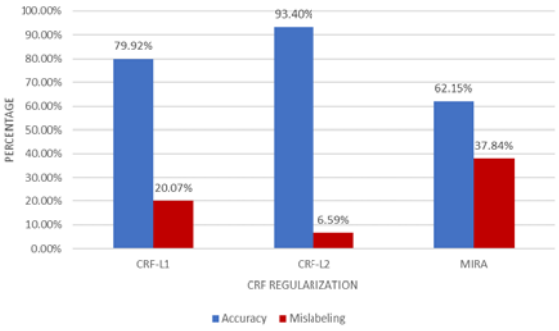


Figure2. Comparison of CRF regularization algorithms

4.5. Experiment in the First-Round (Inference Result Analysis)

Around 2,000 data records and 106 experiment sessions are used for test data. For accurate results test data and train data should bethe same.Inference results are shown:

Table 2.The format oftarget inference output

Observed-status	Time	Target	InferredTarget / Inference Probability
……	……	……	……
clickMenuMyPapers	10s	ViewMyPaperInfo	ViewMyPaperInfo/0.994360
clickPaperInfos&PapeID	5s	ViewMyPaperInfo	ViewMyPaperInfo/0.995209
clickMenuAllPapers	20s	ViewAllPapers	ViewAllPapers/0.953135
clickHideSelection	10s	ViewAllPapers	ViewAllPapers/0.906043
clickEndSession	10s	Test	Test/0.975867
……	……	……	……

Each target inference outputcovers the inferred target and inference probability, generated from the CRF model. We have observed that different feature templates give the different inference accuracy as

result shown in Table 4. The complete feature template is shown in Table 2.

Table4.Mislabeling % of different templates

	Template 1 U01, B01~B04	Template 2 U01~U12	Template 3 U01~U12, B01~B04
%Mislabeling	9.7890% (205/2094)	23.1614% (485/2094)	6.59025% (138/2094)

The CRF model cannot express divergent behaviors with users' real targets.For studying the targets with low inference probability, inference probability should relate to inference accuracy. As results are shown in figure 3 as inference probability range is increased, wrong inference will decrease. It is better to focus on learningobserved-statuses with low inference probability for improving the proficiency of new intention detection in method 1.

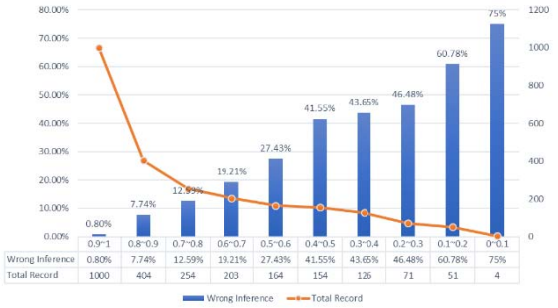


Figure 1. Comparison betweenWrong InferencePercentage and Total Record

4.6. Experiment in the First-round (New Intention Detection)

The first-round experiment is shown some examples for new intention detection:

1) Method 1 to detect new intention;Study observed-statuses with low confidence values i.e. (inference probability <= 0.5). To validate users' divergent behaviors and evaluate them to improve the system, we give some examples here.

a) Example 1: "hide the above section form" is often clicked by users' to hide the selection form.

Table 3. Example segment in the target inference results

Observed-status	Time	Inference Results
clickFilter&FilterAll	30s	FilterPapers /0.633461
clickHideSelection	10s	ViewAPaperInfo /0.362585
clickMenuUploadPaper	60s	UploadPaper /0.861872
clickCommentUploadPaper&PaperExists	M	UploadPaper /0.801465

The observed-status "clickHideSelection" is labeled with inference target "ViewAPaperInfo" with a probability lowest 0.362585, and its preceding observed-status is also labeled with low probability. However, its next observed-statusis labeled with a very high inference probability. Thisobserved-statusof "Hide Selection" can be easily pulled out for analysis. The selection form delays users to see the information page of paper because it is too vast. We analyzed and applied a modification to the system: simply, a link "Expand it" is added to show the complete selection form.

b) On the web-page of "submit/edit a comment" button is clicked twice: The reason of this mistake is that users are not clear about it, so the proposed method is to show a popup message after clicks the button "submit".

c) The user may copy the password with an extra space, this becomesreason forthe wrong password. A possible solution is to prompt the message to show that the password contains a space.

2) New intention detection method 2

To find users' potential new intentions is to study the target transitions is another way.

Table 4. Target transitions in the first-round experiment

Target transition	Existences	Percentage
UploadPaper>ViewMyPaperInfo /UploadPaper>AnyTarget	21/40	52.5%
SubmitComment>ViewMyCommentInfo / SubmitComment>AnyTarget	32/40	80%

To simplify users' behaviors and make efficient transitions the new intention can be expressed as the target transitions, so that system can be modified. E.g., for the target transition "UploadPapper>ViewMyPaperInfo"existencesare 21/40, a new action link can be displayed of the submitted paper, right after the paper is submitted successfully.

3) Common users' erroneous behaviors

It is observed that a common error can be seen asif an erroneous behavior occurs in the observed-status more than 6 times. In the first-round the detected some common erroneous behaviors are:

a) When modifying the information of a paper, no file is uploaded. Users don't want to upload a file while editing the information that causes erroneous behavior. A possible modification is to allow the user to upload no filewhen modifying the information;

b) For submitting the comment,a number of words are not enough when users' is submitting it, so the erroroccurs because specific numbers of words are required. The system should count the words while the user is going to submit it.

4.7. Experiment in the Second-round (System Enhancement)

After the first-round experiment, modifications areapplied, and the system is enhanced to satisfy users' new requirements. A standard CRF model of the second round is build using around 5,000 training data records and around 2,000 to test data to predict the target inference. The combinedtarget inference accuracy is:

Table 5.comparison on target inference accuracy

Experiment	%Mislabeling	%Accuracy
First-Round	6.59025% (138/2094)	93.4097% (1956/2094)
Second-Round	1.9924% (42/2108)	98.0075% (2066/2108)

System improvements in the second-round and estimation of these improvements are following:

1) In the new second-round system after deployment, a link "Expand it" is added for the selection form, to improve users' divergent behavior;

We alsostudiedthe users' behaviors when users went to the page "All Papers", there are some kinds of behaviors are located: a) Filter papers by using the form; b) to filter the paper expand the selection form on all papers; c) others;

2) Target transitions from "Upload/Edit paper" or "Submit/Edit Comments" to "View My Comment/Paper"; In the new evaluated system, a link is added for newly submitted Comment or Paper.Another example of target transition is to add a link of "Download Paper", on the page of all paper's information.

As shown in table 7, system performance is improved in version II, as the rate of mislabeling significantly decreases, the success rate is increased.

CONCLUSION

A methodology of new intention detection and target inference by applying the CRF method is presented in this experiment. The CRF method is used to encode the connections of observable actions, existing targets and context values. We applied a technique to infer targetsby applying the CRF model. We also demonstrate that CRF regularization L1 and L2and MIRA algorithms have different accuracy result, thus L2 regularization gives best results.Furthermore, users' divergent behaviors are labeled with targets in low inference, they will be identified users' potential new intentions detection or system drawbacks on the basis of target inference. Thus, CRF method for detection new intentions and divergent behaviors and system errors make possiblerecommendations for system evolution.

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