A Kind of Authentication Method based on User Web Browsing Features

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Abstract—Traditional authentication methods based on user browsing behaviors consider relatively one-sidedly on user browsing habits. They mainly research on the relationships between the sequences of websites or contents without considering user habits comprehensively. So the accuracy when they distinguish different users’ web browsing behaviors cannot ensure enough safety, which can be further optimized. This paper introduces a new method which studies from favorite websites, contents and periods of browsing time. It uses Apriori algorithm to mine user’s frequent itemsets along with the text classification method and normal distribution to calculate access periods of time. Logic regression algorithm is applied onto user authentication. Experiment shows that detection rate can reach 92.7% while false alarm rate is 6.4%.

Index Terms—Identity authentication, user behavior, web browsing features, frequent itemset.

I. INTRODUCTION

With the development of IT technology, the number of people using online shopping is increasing now. According to the latest IResearch report: “2014 Annual Monitoring Report on China’s Online Shopping Industry” [1], China has become the world’s largest online retail market. Online shopping is gradually changing Chinese people’s consumption habits. But at the same time, the number of fraud cases in online shopping is also growing. “2013 Internet Security Conference” shows that new online shopping frauds have become a primary security threatening to Internet users. In the case of frequent leakage of user password, traditional protecting methods has some weakness, making user authentication one of the key problems of online shopping security. This paper aims to settle the problem of traditional certification methods. The improvement is divided into three parts: replace one-time certification with sustainable certification; introduce a new mining method which analyze user’s browsing habits; improve the method for higher safety.

The first part is about authentication type. Researches on user authentication can be divided into two types: one-time certification and sustainable certification [2]. The former can be classified into following methods: Traditional account, password authentication [3]-[5], Smart card-based authentication [6], the authentication based on biological and behavioral characteristics (e.g. fingerprint, users’ habits of using the mouse [7], [8] and keyboard input [9], [10]). Since the last one cannot be easily imitated, it attracts more academic attention. Anyway, they are all one-time certification, which means the authentication is done in a moment. Once obtained, the authentication is valid forever. So this kind of method is unable to provide high security level for users. Considering of the fact that one-time certification has above weakness, this paper chooses sustainable certification. Sustainable certification is much more complicated, but can offer higher safety, since it does certification work continuously during user operation.

Secondly, this paper introduces a new mining method into identity certification scene. Currently, research based on user browsing behavior is mainly used in scenes like search engine optimization [11], [12] and web page recommendation [13]-[15]. In [11], in order to optimize search engine, a user browsing path is introduced in the form of access graph to determine the most frequent access sequences. Literature [15] uses preference factor for web recommendation based on the browsing patterns mined out by FP tree. Traditional mining method does not adapt to identity certification scene, since it is a must to do individual authentication for each user. So we need to study personal browsing habits and portray behavior patterns, which differs from traditional methods. According to users’ historical browsing records, Literature [2] focuses on the relationship between websites and uses Apriori algorithm to find out potential links among websites. Then it makes identity authentication based on rules combined with Simple CART. Experiment shows that [2] can achieve a detection rate of 91.3% with false positive rate at 10%.

Finally, this paper discusses to the weakness of previous mining methods, and improves it for higher safety. Previous methods mine user browsing feature from the sequences of websites or contents without considering user habits just like [2]. Its accuracy can be further optimized. For instance, there may exists a sequence where some userbrowse the Internet: Baidu.com, Ifeng.com-> Sina.com, which cannot accurately reflect user’s browsing behavior. This is because of the fact that a web site may cover following contents on entertainment, society, science and technology, etc., while each person browse different contents on the same website. For example, user A may has such browsing feature: (Ifeng.com, society)-> (Sina.com, society), while user B has a browsing feature like (Baidu.com, society), (Ifeng.com, entertainment)-> (Sina.com, military). Present methods for mining user browsing feature may generalize A and B’s different browsing features into one feature, where the ability to distinguish the two users’ features is lost. In addition, different users may view specific content at different time. So
time is also a very important factor. Considering the aspects above, this paper improves a new mining method. It uses Apriori to mine out the feature of user web browsing habits based on frequent URLs, contents and time, and uses LR for classification and certification. Experiments show the good feasibility and accuracy of this authentication method.

II. DEFINITIONS

Definition 1 Visit record set \( R \) is a set of webpages browsed by users, denoted by users \( R = \{ r_1, r_2, r_3, ..., r_n \} \). For each element \( r_i \) in \( R \), \( r_i = (url, title, timestamp) \). \( r_i.url \) means the URL of website \( r_i \), \( r_i.title \) means title of \( r_i \) and \( r_i.timestamp \) means it’s timestamp.

Definition 2 Session \( s \) [16] is a set of webpages which the request time of adjacent visit record is less than 30min, denoted by
\[
s = [r_i | r_i.timestamp - r_m.timestamp < 30 \text{min}, r_m \in R].
\]
And the set of \( s \) is denoted as \( S \).

Definition 3 Visit Record Set after Data Processing \( R' \) is a corresponding set of visit records set \( R \), denoted by \( R' = \{ r'_1, r'_2, r'_3, ..., r'_n \} \). For \( r'_i \) in it, \( r'_i = (\text{domain}, \text{content}, \text{time}) \), \( r'_i.\text{domain} \) is the top domain of \( r'_i \), \( r'_i.\text{content} \) is the classification of \( r'_i.\text{title} \), \( r'_i.\text{time} \) is the relative time of \( r'_i \).

Definition 4 Session after Data Processing \( S' \) is a corresponding set of \( s \) in which every visit record is after data processing, denoted by \( S' = \{ r'_1, r'_2, r'_3, ..., r'_n \} \). And the set of \( S' \) is denoted as \( S'' \).

Definition 5 Webpage Class \( P \) is a set of webpages with the same top domain and classification, denoted by
\[
P = \{ (r'_i.\text{domain}, r'_i.\text{content}) | r'_i.\text{domain} = r'_m.\text{domain} \}
\]
\[
= \{ r'_i.\text{domain} \land r'_i.\text{content} = r'_m.\text{content} \}.
\]

Definition 6 Frequent Access URLs \( FU_j \) is a collection contains 15 kinds of top domains which are most frequently accessed by user \( j \), denoted by
\[
FU_j = \{ \text{domain}(r.url) | r \in R \land \text{domain}(r.url) \in \text{top}(15) \}.
\]

Definition 7 Time Page Class \( PT \) is a set of webpages with the same classification of content, \( PT = \{ pt_1, pt_2, ..., pt_l \} \). For each element \( pt_j \) in \( PT \), \( pt_j = (\text{time}, \text{content}) \).

Definition 8 Frequent Access Period of Time \( FT \) is a frequent period of time for the user to access each classification of content, \( FT = \{ f_{t_1}, f_{t_2}, ..., f_{t_{12}} \} \), where \( f_{t_j} \) is user’s frequent period of time for content \( t \).

Definition 9 Support \( fc \) [17]. For transaction \( fc \), \( X, Y \) in the dataset \( D \), Support \( (fc) \) is defined in Function 1, where \( \text{count}(X \cup Y) \) is the number of transaction in \( D \) containing \( X \cup Y \).

\[
\text{support}(X, Y) = \frac{\text{count}(X \cup Y)}{|D|} \quad (1)
\]

Definition 10 Frequent Itemsets \( FC_j \) [17] is a set itemset of user \( j \) which meets \( \delta \), denoted by \( FC_j = \{ fc_i | \text{support}(fc_i) \geq \delta, 1 < i < m \} \), where \( \delta \) is the set support threshold [18].

Definition 11 Feature Value Matrix \( FV_j \). For a session set after data processing which contains \( m \) sessions, each session has a feature value vector \( fv_j = < \text{length}, \text{pun}, \text{mrn}, \text{rpm}, \text{mrrl}, \text{mrml}, \text{mrrms}, \text{mrras} > \) and the meaning of each attribute will be given later.

Definition 12 Set of Frequent Itemset’s Length is a set of frequent itemset’s length which contained in the session \( S''_j \), denoted by \( FC_j.\text{length} = \{ fc_{m}.\text{length} | fc_{m} \subseteq s''_j \land fc_{m} \in FC_j \} \).

Definition 13 Set of Frequent Itemset’s Support is a set of the frequent itemset’s support contained in the session \( S''_j \), \( FC_j.\text{support} = \{ fc_{m}.\text{support} | fc_{m} \subseteq s''_j \land fc_{m} \in FC_j \} \).

For session \( s''_j \in S'' \), every attributer’s meaning in the feature value vector is as follows:

- length: the number of pages contained in the session \( s''_j \);
- pun: the number of frequent access URLs contained in the session \( s''_j \);
- mrn: the number of frequent access URLs contained in the session \( s''_j \);
- rpm: the number of frequent access URLs contained in the session \( s''_j \);
- mrrl: maximum length of frequent itemset contained session \( s''_j \);
- mrml: maximum length of frequent itemset contained session \( s''_j \);
- mral: average length of frequent itemset contained session \( s''_j \);

\[
\text{mral} = \frac{\sum p}{\text{count}(FC_j.\text{length})} \quad (2)
\]

where \( \text{count}(FC_j.\text{length}) \) means the number of elements in \( FC_j.\text{length} \);

- mrmr: maximum support of frequent itemset contained in session \( s''_j \);
- mrms: maximum support of frequent itemset contained in session \( s''_j \);
- mras: average support of frequent itemset contained in session \( s''_j \), its function is as follows:

\[
\text{mras} = \frac{\sum p}{\text{count}(FC_j.\text{support})} \quad (3)
\]

where \( \text{count}(FC_j.\text{support}) \) means the number of elements in \( FC_j.\text{support} \);

- mtn: number of frequent access period of time matched by session \( s''_j \);
- target: target column, if \( s''_j \) is legal, we record it as 1, else 0.

In this paper, the first nine elements of \( fv_j \) correspond to the variables vector in \( f_j : X \rightarrow Y \), and \( <\text{target}> \) means target vector \( Y \). The user browsing feature is shown as a
III. CONSTRUCTION AND AUTHENTICATION OF UWBF

In this section, we mainly focus on how collected data is used in extracting user web browsing features and identify authentication.

A. Data Processing

This paper collects one month’s visit records of 10 users. It uses 30 min as the maximum interval of a session [2], [16]. Besides, for the purpose of mining more potential relationships of (website, content), this paper extracts the top domain and classifies the websites for generalizing.

1) Session partition: According to Definition 1, we collect original records of each user. And then we generate each user’s sessions according to Definition 2 to form S. For user j, its session set is

\[ S_j = [s_1, s_2, ...] = \{ [r_1, r_2, ... r_ε], [r_{ε+1}, r_{ε+2}, ... r_{ε+ν}], ... \} \]

2) Webpage procession: Here, we convert every record r into the structure of p in Definition 3:

- **Step 1:** top domain extraction, which means extract top domain of r.url.
- **Step 2:** content extraction, which means classify the content of record according to its title. In this step, we refer the major news sites as well as the input methods’ thesaurus, define 12 classes in advance and use Sogou lab’s text classification samples and some articles on the network as the training text. There are 10 articles under each classification. Then we extract corresponding keywords from every user’s article and classify web pages by matching the keywords in the title.
- **Step 3:** relative time computing. To obtain every day’s frequent access period of time of every content, we need to convert r.timestamp to the milliseconds from every day.

For instance, there is a record r stored in the database: (http://news.163.com/14/1103/18/AAS5S2T800014SEH.html, the hero in Wenchuan earthquake is involved in the in the fraud trial of 460000 yuan, 36510608). After webpage processing, it changes to (news.163.com, society, 36661272).

And we generate the final session set \( S^* = \{ s_1', ... s_n' \} \).

3) Page class merger: In fact, page class merger is a process to generalize records. After this step, two different records \( r_j \) and \( r_j' \) will become \( r_j'' \) and \( r_j''' \) which have the same details except the relative time.

For the purpose of mining user’s frequent items sets, this paper merges \( r_j'' \) and \( r_j''' \) into one webpage set \( P \), so a webpage set may contain many records. For instance, there is a session set after the step of webpage processing:

\[ S_j' = \{ [p_1, ... , p_m] \} \]. We merge the same webpages into one webpage class and let it replace the original records, and generate a new session set \( S_j'' = \{ [p_1, ... , p_m] \} \).

B. Feature Extraction

In the stage of feature extraction, we extract users’ features from three aspects: frequent access URLs, (website, content) and (content, frequent access period of time).

1) The mining of frequent itemsets: We find that each user has different favorite contents in different websites. For instance, user A prefers military news in news.ifeng.com after reading social news in news.163.com and financial news in news.qq.com. Such frequent itemsets are different to each user. We regard the relationship of (website, content) as the bases for user identify authentication.

During the mining of frequent itemsets, the correct selection of support threshold \( δ \) has a great influence on (false alarm rate (FAR) and detection (DR)). So we need to find a proper \( δ \) to balance them.

After this step, we may discovery such a frequent set like \( P_1, P_2, P_3 \), namely \((\text{domain}_1, \text{content}_1), (\text{domain}_2, \text{content}_2), (\text{domain}_3, \text{content}_3)\).

2) The mining of frequent periods of time: A statistic on frequent access periods of time of different contents for each user is necessary in this step. Since every user is used to browse different contents in specific period of time, we use the FT in Definition 6 to dig out them, and save them in the form of Definition 7. For a user, we assume that the period of time of a content he views is subject to a normal distribution process.

For \( p_t \in PT \) , \( f_{jt} \in FT \) and \( p_t, \text{content} = ft, \text{content} \).

\[ f_{jt}, \mu = \frac{\sum_{i=1}^{m} p_{i, \text{time}}}{m} \] \tag{4}

\[ f_{jt}, \sigma^2 = \frac{\sum_{i=1}^{m} (p_{i, \text{time}} - \mu)^2}{m - 1} \] \tag{5}

where \( m \) means the number of elements in \( FT \).

For example, there is such an element in \( FT \) of user A: \( f_{t_3} = (\text{content}, \mu, \sigma^2) \), this means user A is accustomed to browse the content in the period of time of \( (\mu - 3\sigma, \mu + 3\sigma) \).

C. Authentication Based on User Browsing Feature

During the phase of constructing the method based on user web browsing feature, we need to choose a proper classification algorithm which is combined with the feature values computed in Section III.B. So we can judge whether the session is legal or not. Through the comparative experiments, we choose the logistic regression algorithm [19] (LR) as the classifier.

LR is a typical binary-class classification algorithm, which is relatively simple and easy to explain, and rarely occurs over fitting. It is actually a process of learning function \( f: X \rightarrow Y \). We give n-tuple variable vector \( X = \langle X_1, X_2, ..., X_n \rangle \) and an m-tuple target vector \( Y = \langle Y_1, Y_2, ..., Y_m \rangle \) in advance. LR’s responsibility is to learn a function, which can fit \( Y \) furthest according to \( X \) we have given before.

We use LR as a binary-classifier. Once test data is obtained, we will compute \( y \) according to the function as follows [19]:

\[ y = w_0 + w_1 * x_1 + w_2 * x_2 + \cdots + w_n * x_n \] \tag{6}

where \( x_1, x_2, \cdots, x_n \) are the features of a sample data. Then
we use the Function \( \text{sigmoid} \) to do the following things:

\[
\sigma(y) = \frac{1}{1 + \exp(y)}. \tag{7}
\]

Domain of Function \( \text{sigmoid} \) is \((-\infty, +\infty)\) and domain of value is \((0, 1)\).

In order to eliminate the influence of authentication caused by the difference of feature values’ range, we normalize feature values before using the LR first so that every value can be transformed into the range of \([0, 1]\). Its function is as follows:

\[
x_k \mapsto f(x_k) = \frac{x_k - \min x_k \cdot 1}{\max x_k - \min x_k}, \tag{8}
\]

where \(x_{\max} = \max(x_1, x_2, ..., x_n)\), \(x_{\min} = \min(x_1, x_2, ..., x_n)\).

For the authentication algorithm of this paper UWBF (a kind of authentication algorithm based on user web browsing features), data is the train session set after normalization. It uses LR and frequent itemsets, frequent access URLs, frequent access periods of time of legal user to learn a matrix on feature values’ weights. The specific process of the authentication method is shown in algorithm 1.

Algorithm 1: UWBF

\textbf{Input:} session set \( S \), a legal user’s frequent itemsets \( FC \), the legal user’s frequent access URLs and frequent access periods of time \( FT \)

\textbf{Output:} the matrix of feature values’ weights \( w \), array \( \text{score}_{\text{legal}} \)

1. \textbf{for all} \( s_i \) in \( S \) \textbf{do}
2. \hspace{1em} Calculate each element value in \( FV \),
3. \hspace{2em} \( \text{mrtl} \leftarrow 0 \)
4. \hspace{2em} \( \text{mrts} \leftarrow 0 \)
5. \hspace{2em} \( \text{ftm} \leftarrow \text{fromFU(FU)} \)
6. \hspace{2em} \( \text{ftmr} \leftarrow \text{fromFU(Aver(FU))} \)
7. \hspace{2em} \( \text{mtn} \leftarrow \text{fromFT(FT)} \)
8. \hspace{2em} \text{Save all attributes into } FV,
9. \textbf{end for}
10. \textbf{for all} \( \text{element in ten-tuple } FV \text{, do} \)
11. \hspace{1em} Create and set value matrix
12. \hspace{2em} \( \text{dataMatrix}[] \leftarrow \text{createDataMatrix(FV)} \)
13. \hspace{2em} \( \text{labelMatrix}[] \leftarrow \text{createDataMatrix(FV)} \)
14. \hspace{2em} \( \text{weightMatrix}[] \leftarrow \text{createDataMatrix(FV)} \)
15. \hspace{1em} \textbf{end for}
16. \textbf{for all} \( FV_i \) in \( \text{FV} \), \textbf{do}
17. \hspace{1em} Calculate the session’s score according to \( \omega \)
18. \hspace{2em} \( \text{score}_{\text{legal}}[i] \leftarrow \text{calc}(\omega) \)
19. \hspace{1em} \textbf{end for}

IV. EXPERIMENT RESULT

Experimental environment: Intel (R) Core (TM) i3CPU (3.23GHz), 4GB memory, Windows8 operating system, Java development language, eclipse development environment.

Experimental data: web browsing records collected from 10 users within 4 weeks. For each webpage, we collect its title, URL and timestamp. According to Section III.A, each user can form a collection of about 200 sessions after data processing. We suppose that one of 10 users is legal while the other users are not.

Since the effect of identify authentication may be impacted by \( \delta \) and the algorithm of classification. For the purpose of having a better authentication effect, this paper does the experiments from three aspects: (1) choose a proper \( \delta \); (2) choose a suitable algorithm of classification according to the contrast experiments; (3) use the computed \( \delta \) and algorithm of classification to authenticate.

A. Choice of Support Threshold

D. Identify Authentication

We actually use LR to train and learn the authentication method based on user’s browsing features. In this section, we need to compute a score’s threshold for classification. If the computed score is in the classification threshold, we regard it as a legal session, otherwise we regard it as illegal. So the identify authentication will be divided into two parts.

1) The choice of classification threshold: Before choosing the classification threshold, we get the matrix of weights \( w(w_0, w_1, w_2, ..., w_9) \) and feature value vector \( f_{v_i} \) of session \( f \) to compute its score, the function is as follows:

For \( f_{v_i} \in FV \),

\[
\text{score} = w_0 + w_1 * f_{v_i, \text{length}} + w_2 * f_{v_i, \text{pun}} + ... + w_9 * f_{v_i, \text{mtn}} \tag{9}
\]

By using Function 9 and Definition 11, we can get the train set’s feature value set \( FV_{\text{train}} \) and compute the legal sessions’ scores: \( \text{score}_{\text{legal}} = \{ \text{score}_{\text{legal}}, \text{score}_{\text{legal}}, ..., \text{score}_{\text{legal}} \} \).

Then we compute the threshold of classification and the function is as follows:

\[
\delta = \frac{1}{m} \sum_{i=1}^{m} \text{score}_{\text{legal}}[i] - \text{score}\]

\[
\delta = \frac{1}{m} \sum_{i=1}^{m} (\text{score}_{\text{legal}}[i] - \text{score}) \tag{10}
\]

where \( M \) means the length of array \( \text{score}_{\text{legal}} \).

In this paper, the classification threshold is set to \([\text{score} \in \gamma, 1]\), which means that if the session’s score is in this threshold, we regard it as legal, otherwise we regard it as illegal.

2) The calculation of session’s score: After using the first step of the construction of the authentication method based on user browsing feature, we generate every session’s set of feature values \( FV_{\text{test}} \). Then we compute the matrix of weights according to UWBF and every session’s score in the test session set according to Function 9. Finally, we judge whether every session is legal or not according to the classification threshold.
We use FAR as abscissa and DR as ordinate. In Fig. 1, the blue curve shows the relationship of DR and FAR when the support threshold changes, and the red dotted line is EER which means $y=x$. Through Fig. 1, we can find that when FAR=DR=0.102, two curves intersect, and $\delta$ at this moment is the optimal threshold [20]. Then by Fig. 2 which shows the relation between FAR and $\delta$, we can find that when FAR=0.0102, $\delta = 0.0257$. We set it as the support threshold for mining frequent itemsets.

**Experiment 1:** Based on their own data, two algorithms’ contrastive performances in authentication are shown in Fig. 4. UWBF’s FAR is 6.4%, DR is 92.7% while FAR of WS is 10%, DR is 91.3%. What’s more, the AUC [20] (Area under the Curve of ROC) of UWBF is 0.983 while the AUC of [2] is 0.952.

**Experiment 2:** Based on this paper’s data, the authentication effects of UWBF and WS are shown in Fig. 5. UWBF’s FAR is 10%, DR is 93.6% while FAR of WS is 10%, DR is 87%. And UWBF’s AUC is 0.983 while the AUC of [2] is 0.932.

### B. Choice of Classification

In the period of authentication, there is a need to select a suitable algorithm of classification. We use this paper’s data and compare performances of LR, decision tree and KNN by showing their authentication effects in ROC. As shown in Fig. 3:

![ROC of each algorithm](image)

Fig. 3. ROC of each algorithm.

From Fig. 3, we can see that performance of LR is the best, so we choose LR as this paper’s algorithm of classification.

### C. Identify Authentication

In order to compare UWBF with WS (the algorithm of [2]) which based on sequences of webpages, we conduct two experiments with the support threshold $\delta$ of 0.0257 and present the experimental results in the form of ROC curves.

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**V. CONCLUSION**

This paper proposes a kind of authentication method based on user web browsing feature. It combines user’s favorite websites, content and period of time and regards them as a whole entity to analyze. We use Apriori to mine out every user’s browsing features and use LR to construct a classifier to do authentication. Experiments show that compared with method which considering the links between websites, this paper has a better performance in identity authentication and reflecting different users’ web browsing features. It can achieve higher DR under smaller FAR.

In future work, we will study more on sequence association rule mining. Multipliers can be especially confusing.

### REFERENCES


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