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INDEPENDENT COMPONENT ANALYSIS AND ROUGH FUZZY BASED APPROACH TO WEB USAGE MINING

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ABSTRACT

Web Usage Mining is that area of Web Mining which deals with the extraction of interesting knowledge from logging information produced by Web servers. A challenge in web classification is how to deal with the high dimensionality of the feature space. In this paper we present Independent Component Analysis (ICA) for feature selection and using Rough Fuzzy for clustering web user sessions. It aims at discovery of trends and regularities in web users' access patterns. ICA is a very general-purpose statistical technique in which observed random data are linearly transformed into components that are maximally independent from each other, and simultaneously have "interesting" distributions. Our experiments indicate can improve the predictive performance when the original feature set for representing web log is large and can handling the different groups of uncertainties/impreciseness accuracy.

KEY WORDS
Web Usage Mining; Independent component analysis; Rough Sets; Fuzzy rough sets;

1. Introduction

With the rapid growth of information on the World Wide Web, automatic classification of web pages has become important for effective indexing and retrieval of web documents. Soft computing is a consortium of methodologies that works synergistically and provides, in one form or another, flexible information processing capability for handling real life ambiguous situations. The principal soft computing tools include fuzzy sets, artificial neural networks, genetic algorithms and rough set theory [1]. Web usage data includes data from web server access logs, proxy server logs, browser logs, user profiles, registration files, user sessions or transactions, user queries, bookmark folders, mouse-clicks and scrolls, and any other data generated by the interaction of users and the web. Web using mining (WUM) works on user profiles, user access patterns and mining navigation paths which are being heavily used by e-commerce companies for tracking customer behavior on their sites [1]. Web usage mining of the data generated by the users' interactions with the Web, typically represented as Web server access logs, user profiles, user queries and mouse-clicks. This includes trend analysis (of the Web dynamics information), and Web access association/sequential pattern analysis [2]. The clustering problem is a fundamental problem that frequently arises in a great variety of fields such as pattern recognition, machine learning, and data mining. Pre-processing the trend signals for the purpose of noise removal, qualitative interpretation and dimension reduction is now an important step in developing computer-aided systems for fault detection and diagnosis. There are two aspects in dimension reduction of process dynamic trends: feature extraction from a trend of an individual variable and removal of dependencies among a number of correlated and sometimes redundant variables [3]. Independent component analysis (ICA) aims at extracting unknown hidden factor/components from multivariate data using only the assumption that the unknown factors are mutually independent [4]. Rough sets are a tool to deal with inexact, uncertain or vague knowledge. Specifically, it provides a mechanism to represent the approximations of concepts in terms of overlapping concepts.

Soft computing methodologies, involving fuzzy sets, neural networks, genetic algorithms, rough sets, and their hybridizations, have recently been used to solve data mining problems. They strive to provide approximate solutions at low cost, thereby speeding up the process. A categorization has been provided based on the different soft computing tools and their hybridizations used, the mining function implemented, and the preference criterion selected by the model [5]. A novel approach using independent component analysis for dimension reduction from dynamic trend signals has been presented. However, ICA has been restricted to unsupervised cases [6].

The rest of the paper is organized as follows: Section 2 deals with web clustering and features selection. The Rough Sets, Fuzzy Set and Rough Fuzzy are discussed in Section 3. Section 4 provides an experimental design. Sections 5 describe experimental results and discussions and conclusion in Section 6.

2. Web Clustering and Features Selection

2.1. Web clustering

Clustering pertains to unsupervised learning, where no predefined classes are assigned. The key requirement is the need for a good measure of similarity between the instances/patterns. The problem is to group *n* patterns into *c* desired clusters, such that the data points within clusters are more similar than across clusters. Scalable clustering algorithms pertain to working with large volumes of high dimensional data that is inherent to data mining problems [2]. The importance of clustering to Web mining, specifically in the domains of Web Usage mining, make Web clustering an interesting topic of research. This includes clustering of access logs the involves overlapping clusters.

2. 2 Independent component analysis (ICA)

In a classification problem, the number of features can be quite large, many of which can be irrelevant or redundant. A relevant feature is defined in [7] as one removal of which deteriorates the performance or accuracy of the classifier, and an irrelevant or redundant feature is not relevant. These irrelevant features could deteriorate the performance of a classifier that uses all features since irrelevant information is included inside the totality of the features. Thus the motivation of a feature selector is (i) *simplifying* the classifier by the selected features; (ii) *improving or not significantly reducing* the accuracy of the classifier; and (iii) *reducing* the dimensionality of the data so that a classifier can handle large values of data [6]. Many approaches as feature selectors have been proposed.

Independent component analysis (ICA) for dimension reduction is to separate these independent components (ICs) from the monitored variables. Introduction of ICA concepts in the early 1980s in the context of neural networks and array signal processing. ICA was originally developed to deal with problems that are closely related to the real world 'cocktail-party' problem. ICA is a method for automatically identifying the underlying factors in a given data set. Dimension reduction using ICA is based on the idea that these measured variables are the mixtures of some independent variables. When given such a mixture, ICA identifies those individual signal components of the mixture that are unrelated. Given that the only unrelated signal components within the signal mixture are the voices of different people. ICA is based on the assumption that source signals are not only uncorrelated, but are also 'statistically independent' [8].

ICA techniques provide statistical signal processing tools for optimal linear transformations in multivariate data and these methods are well-suited for feature extraction, noise reduction, density estimation and regression [9]. The ICA problem can be described as follows, each of h mixture signal $x_1(k), x_2(k),\ldots,x_h(k)$ is a linear combination of q independent components $s_1(k), s_2(k),\ldots,s_h(k)$, that is , X = AS where A is a mixing matrix. Now given X, to compute A and S. Based on the following two statistical assumptions, ICA successfully gains the results: 1) the components are mutual independent; 2) each component observes nongaussian distribution. By X = AS, we have $S = A^{-1}X=WX$ (where $W = A^{-1}$). The take is to select an appropriate W which applied on X to maximize the nongaussianity of components. This can be done in an iteration procedure.

Given a set of *n*-dimensional data vectors $[X^{(1)},X^{(2)},\ldots,X^{(N)}]$, the independent components are the directions (vectors) along which the statistics of projections of the data vectors are independent of each other. Formally, if A is a transformation from the given reference frame to the independent component reference from then

$$X = As$$

Such that

$$p(s) = \prod p_a(s_i),$$

where $p_a(.)$ is the marginal distribution and *p*(s) is the joint distribution over the *n*-dimensional vector *s*. Usually, the technique for performing independent component analysis is expressed as the technique for deriving one particular W,

$$Y = Wx,$$

Such that each component of y becomes independent of each other. If the individual marginal distributions are non-Gaussian then the derived marginal densities become a scaled permutation of the original density functions if one such *W* can be obtained. One general learning technique [10; 11] for finding one *W* is

$$\Delta W = \eta(I - \phi(y)y^T)W,$$

Where $\phi(y)$ is a nonlinear function of the output vector y (such as a cubic polynomial or a polynomial of odd degree, or a sum of polynomials of odd degrees, or a sigmoidal function) [12].

3. Rough Sets, Fuzzy Set and Rough Fuzzy

3.1 Rough Sets

Rough sets are characterized by their ability for granular computation. In rough set theory a concept *B* is described by its "lower" $(\underline{B})$ and "upper" $(\overline{B})$ approximations defined with respect to some indiscernibility relation. Rough set theory [12] provides an effective means for analysis of data by synthesizing or constructing approximations (upper and lower) of set concepts from the acquired data. The key notions here are those of ''information granule'' and ''reducts''. Information granule formalizes the concept of finite precision representation of objects in real life situation, and reducts represent the core of an information system (both in terms of objects and features) in a granular universe [13].

Let $X = \{x_1,\ldots,x_n\}$ be a set of *U* and *R* an equivalence relation on *X*. As usual, *X/R* denotes the quotient set of equivalence classes, which form a partition in *X*, i.e. *xRy* means the *x* and *y* cannot be took apart. The notion of *rough set* [14] born to answer the question of how a subset *T* of a set *X* in *U* can be represented by means of *X/R*.. It consists of two sets:

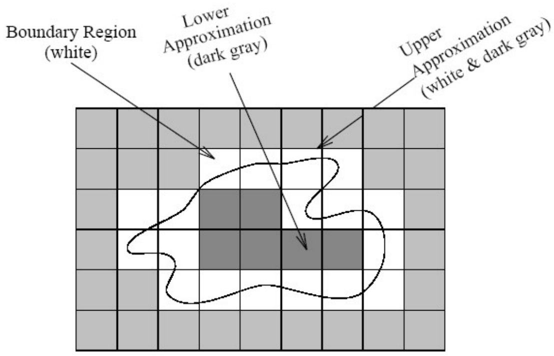

Figure 1: Rough Representation of a Set with Upper and Lower Approximations

$$RS^*(T) = \{[x]_R \mid [x]_R \cap T \neq 0\} \quad (1)$$

$$RS_*(T) = \{[x]_R \mid [x]_R \subseteq T\} \quad (2)$$

where $[x]_R$ denotes the class of elements $x, y \in X$ such that *xRy*. $RS^*(T)$ and $RS_*(T)$ are respectively the *upper* and *lower approximation* of T by *R*, i.e.

$$RS_*(T) \subseteq T \subseteq RS^*(T) \quad (3)$$

Other operations over rough sets include:

- Negative region of $X : U - RS^*(X)$.
- Boundary region of $X : RS^*(X) - RS_*(X)$.
- Quality of approximation of *X* by RS_* and

$$RS^* : \mu_R S(X) = \frac{card(RS^*(X))}{card(RS_*(X))}$$

3.2. Fuzzy Sets

Fuzzy theory provided a mechanism for measuring the degree to which an object belongs to a set by introducing the "membership degree" as a characteristic function $\mu_A(x)$ which associates with each point *x* a real number in the range [0,1]. The nearer the value of $\mu_A(x)$ to unity, the larger the membership degree of *x* in the set *A*.

Let assume *X* be a set, then two different *crisp* versions of a fuzzy set *A* can be define, namely $\overline{A} = \{(x, \mu_{\overline{A}} \mid x \in X\}$ and $\underline{A} = \{(x, \mu_{\underline{A}} \mid x \in X\}$ where

$$\mu \overline{A}(x) = \begin{cases} 1 & \mu_A(x) \geq 0.5 \\ 0 & \mu_A(x) < 0.5 \end{cases} \quad (4)$$

and

$$\mu_{\underline{A}}(x) = \begin{cases} 1 & \mu_A(x) < 0.5 \\ 0 & \mu_A(x) \geq 0.5 \end{cases} \quad (5)$$

Denote $A \subset X$ and $B \subset X$ two fuzzy sets, i.e. $A = \{(x_i, \mu_A(x_i)), i = 1, ..., n\}$ and $B = \{(x_i, \mu_B(x_i)), i = 1, ..., n\}$, the operations on fuzzy sets are extensions of those used for conventional sets (intersection, union, comparison, etc.). The basic operations are the intersection and union as defined as follows:

The membership degree of the *intersection* $A \cap B$ is

$$\mu_{A \cap B}(x) = \min\{\mu_A(x), \mu_B(x)\} \quad x \in X \quad (6)$$

The membership degree of the *intersection* $A \cup B$ is

$$\mu_{A \cup B}(x) = \max\{\mu_A(x), \mu_B(x)\} \quad x \in X \quad (7)$$

Furthermore, a common measure of similarity between two fuzzy sets *A* and *B* is the l^p-distance, defined as follows [15]. The l^p-distance between two fuzzy sets *A* and *B* is given by

$$l^p(A, B) = \left(\sum_{i=1}^{n} \mid \mu_A(xi) - \mu_B(xi) \mid^p\right)^{\frac{1}{p}} \quad (8)$$

if *p*=1 the l^p-distance reduces to the fuzzy Hamming distance.

The fuzzy membership functions corresponding to the informative regions are stored as cases. A collection of fuzzy sets, called fuzzy space, defines the fuzzy linguistic values or fuzzy classes. A sample fuzzy space of five membership function is shown in Figure 2.

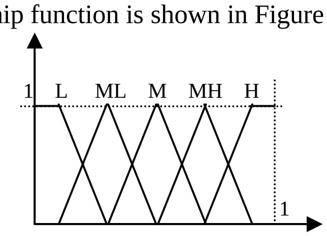

Figure 2: A fuzzy space of five membership function

3.3. Rough Fuzzy sets

In any classification task the aim is to form various classes where each class contains objects that are not noticeably different. These indiscernible or non-distinguishable objects can be viewed as basic building blocks (concepts) used to build up a knowledge base about the real world [16].

In this paper we propose the rough fuzzy sets, realizing a system capable to efficiently cluster data coming from image analysis tasks. The hybrid notion of rough fuzzy sets comes from the combination of two models of uncertainty like vagueness by handling rough sets and fuzzy sets. Rough sets embody the idea of indiscernibility between objects in a set, while fuzzy sets model the ill-definition of the boundary of a sub-class of this set.

The *rough-fuzzy set* is the generalization of rough set in the sense that here the output class is fuzzy. Let *X* be a set, *R* be an equivalence relation defined on *X*, and the output class $A \subseteq X$ be a fuzzy set. The rough-fuzzy set is a tuple $\langle \underline{R}(A), \overline{R}(A) \rangle$, where the lower approximation

$\underline{R}(A)$ and the upper approximation $\overline{R}(A)$ are fuzzy sets of X/R, with membership functions defined in [17, 18] by

$$\mu_{\underline{R}(A)}([x]_R) = \inf\{\mu_A(x) \mid x \in [x]_R\} \quad \forall x \in X \quad (9)$$

and

$$\mu_{\overline{R}(A)}([x]_R) = \sup\{\mu_A(x) \mid x \in [x]_R\} \quad \forall x \in X \quad (10)$$

Here, $\mu_{\underline{R}(A)}(x)$ and $\mu_{\overline{R}(A)}(x)$ are the membership values of $[x]_R$ in $\underline{R}(A)$ and $\overline{R}(A)$, respectively.

The rough-fuzzy membership function of a pattern $x \in X$ for the fuzzy output class $A_c \subseteq X$ is defined as

$$l_{Ac}(x) = \frac{\| F \cap A_c \|}{\| F \|}, \quad (11)$$

Where $F = [x]_R$, and $\| A_c \|$ implies the cardinality of the fuzzy set A_c. Important properties of the rough-fuzzy membership functions that can be exploited in classification task [19].

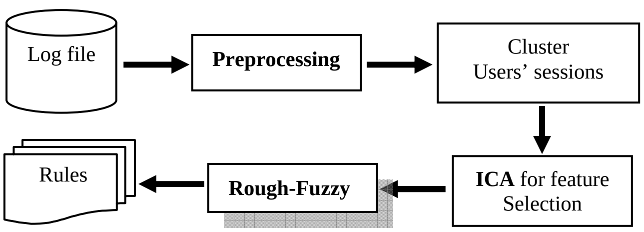

Figure 3: Framework for web usage mining.

4. Experimental Design

The problem is solved in two steps: 1) feature reduction from measured data; 2) clustering based on selected feature. For the first step, ICA, mostly used in feature reduction from time series data, is a statistical and computational technique for revealing hidden factors that underlie sets of random variables, measurements, or signals [9].

5. Experimental Set Up and Results

The prediction models that we build are based on web log data that corresponds with users' behavior. They are used to make prediction for the general user and are not based on the data for a particular client. This prediction requires the discovery of a web users' sequential access patterns and using these patterns to make predictions of users' future access. We will then incorporate these predictions into the web prefetching system in an attempt to enhance the performance.

```
1102801060.863  1897600  172.16.1.98  TCP_IMS_HIT/304 203  GET
http://asclub.net/images/main_r4_c11.jpg - NONE/- image/jpeg
1102801060.863  1933449 172.16.1.183 TCP_MISS/404 526 GET
 http://apl1.sci.kmitl.ac.th/robots.txt -DIRECT/161.246.13.86 text/html
1102801060.863 1933449 172.16.1.183  TCP_REFRESH_HIT/200
3565  GET ttp://apl1.sci.kmitl.ac.th/wichitweb/spibigled/spibigled.html
- DIRECT/161.246.13.86 text/html
```

Figure 4: Sample web log data

The experiment used web data collected from www.dusit.ac.th web server (see example in Figure 4) during 1 December 2004 – 31 December 2004. The total number of web pages with unique URLs is equal to 314 URLs, and there are 13,062 web log records. These records are used to construct the user access sequences (Figure 5). The user session is split into training dataset and testing dataset. The training dataset is mined in order to extract rules, while the testing dataset is considered in order to evaluate the predictions made based on these rules.

5.1 Web log pre-processing

Web log files contain a large amount of erroneous, misleading, and incomplete information. This step is to filter out irrelevant data and noisy log entries. Elimination of the items deemed irrelevant by checking the suffix of the URL name such as gif, jpeg, GIF, JPEG, jpg, JPG. Since every time a Web browser downloads an HTML document on the Internet, several log entries such as graphics and script are downloaded too. In general, a user does not explicitly request all of the graphics that are in the web page, they are automatically down-loaded due to the HTML tags. Since web usage mining is interested in studying the user's behavior, it does not make sense to include file requests that a user does not explicitly request. The HTTP status code returned in unsuccessful requests because there may be bad links, missing or temporality inaccessible pages, or unauthorized request etc: 3xx, 4xx, and 5xx. Executions of CGI script, Applet, and other script codes. We also eliminated enough Meta data to map these requests into semantically meaningful actions, as these records are often too dynamic and contain insufficient information make sense to decision makers.

5.2 Session identification

After the pre-processing, the log data are partitioned into user sessions based on IP and duration. Most users visit the web site more than once. The goal of session identification is to divide the page accesses of each user into individual sessions. The individual pages are grouped into semantically similar groups. A user session is defined as a relatively independent sequence of web requests accessed by the same user [20]. Fu et al. [21] identify a session by using a threshold idle time. If a user stays inactive for a period longer than the identified *max_idle_time*, subsequent page requests are considered to be in another episode, thus another session. Most researchers use heuristic methods to identify the Web access sessions [22] based on IP address and a time-out not exceeding 30 minutes for the same IP Address. A new session is created when a new IP address is encountered after a timeout. Catledge and Pitkow [23] established a timeout of 25.5 minutes based on empirical data. In this paper, we use IP address time-out of 30 minutes to generate a new session. This stage we convert ulr name to numeric. Figure 5 show each session have URL that user visited such as session #1 visit URL 900, 586, 594 and 618 respectively.

Session #1 : 900, 586, 594, 618
Session #2 : 900, 868, 586
Session #3 : 868, 586, 594, 618
Session #4 : 594, 618, 619
Session #5 : 868, 586, 618, 900

Figure 5: User session from data set.

We assume the access pattern of a certain type of user can be characterized by a certain minimum length of a user's transaction, and that the corresponding future access path is not only related to the last accessed URL. Therefore, users with relatively short transactions (e.g. 2-3 accesses per transaction) should be handled in a different way from users with long transactions (e.g. 10-15 accesses per transaction) [24]. In this work, we proposed a case definition design based on the transaction length. User transactions with lengths of less than 3 are removed because it is too short to provide sufficient information for access path prediction [24].

6. Experimental Results

The web access log files from the web site www.dusit.ac.th are used for our experimental study. The data consists of 108 URLs that are selected from visited more than 10 users. The information about the users who have visited a web site is recorded in the related web server log files. The log files contain the raw data of the usage details that forms the basis for click-stream data for the purpose of mining. Training set has 2063 sessions and we got 455 sessions after are removed URL with lengths of less than 3 are removed. Test set has 590 sessions and we got 146 sessions after are removed URL with lengths of less than 3 are removed. More detail in Table 1.

Table 1: Experiment results

Items	Training Set	Test Set
No. of records	7803	5259
No. of URLs	2063	590
No. of sessions	455	146
Maximum Session Length	50	28
Average Session Length	6.32	5.91

From Figure 2, we can be represented as vectors. In De and Krishna [25] proposed a method of clustering the clicks of user navigations.

$$S_1 = \{1,1,1,0,0,1\};$$
$$S_2 = \{1,0,0,0,1,1\};$$
$$S_3 = \{1,1,1,0,1,0\};$$
$$S_4 = \{0,1,1,1,0,0\};$$
$$S_5 = \{1,0,1,0,1,1\};$$

The similarity classes are as follow:

$$sim(S_1,S_2) = \frac{2}{5} = 0.4,\ sim(S_1,S_3) = \frac{3}{5} = 0.6,$$
$$sim(S_1,S_4) = \frac{2}{5} = 0.4,\ sim(S_1,S_5) = \frac{3}{5} = 0.6,$$
$$sim(S_2,S_3) = \frac{2}{5} = 0.4,\ sim(S_2,S_4) = \frac{0}{6} = 0,$$
$$sim(S_2,S_5) = \frac{3}{4} = 0.75,$$
$$sim(S_3,S_4) = \frac{2}{5} = 0.4,\ sim(S_3,S_5) = \frac{3}{5} = 0.6,$$
$$sim(S_4,S_5) = \frac{1}{5} = 0.17$$
$$\underline{R}(s_1) = \{s_1,s_3,s_5\},\ \underline{R}(s_2) = \{s_2,s_5\},$$
$$\underline{R}(s_3) = \{s_1,s_3,s_5\},\ \underline{R}(s_4) = \{s_4\},$$
$$\underline{R}(s_5) = \{s_1,s_2,s_3,s_5\}$$
$$\overline{R}(s_1) = \{s_1,s_3,s_5\},\ \overline{R}(s_2) = \{s_2,s_5\},$$
$$\overline{R}(s_3) = \{s_1,s_3,s_5\},\ \overline{R}(s_4) = \{s_4\},$$
$$\overline{R}(s_5) = \{s_1,s_2,s_3,s_5\}$$
$$\overline{R}\overline{R}(s_1) = \{s_1,s_2,s_3,s_5\},\ \overline{R}\overline{R}(s_2) = \{s_1,s_2,s_3,s_5\},$$
$$\overline{R}\overline{R}(s_3) = \{s_1,s_2,s_3,s_5\},\ \overline{R}\overline{R}(s_4) = \{s_4\},$$
$$\overline{R}\overline{R}(s_5) = \{s_1,s_2,s_3,s_5\}$$
$$\overline{R}\overline{R}\overline{R}(s_1) = \{s_1,s_2,s_3,s_5\},$$
$$\overline{R}\overline{R}\overline{R}(s_2) = \{s_1,s_2,s_3,s_5\},$$
$$\overline{R}\overline{R}\overline{R}(s_3) = \{s_1,s_2,s_3,s_5\},\ \overline{R}\overline{R}\overline{R}(s_4) = \{s_4\},$$
$$\overline{R}\overline{R}\overline{R}(s_5) = \{s_1,s_2,s_3,s_5\}$$

We see that two consecutive upper approximation for $\{s_1\},\{s_2\},\{s_3\},\{s_4\}$ *and* $\{s_5\}$ are same. We get the similarity upper approximation for $\{s_1\},\{s_2\},\{s_3\},\{s_4\}$ *and* $\{s_5\}$ as

$S_1 = \{s_1,s_2,s_3,s_5\}$, $S_2 = \{s_1,s_2,s_3,s_5\}$,
$S_3 = \{s_1,s_2,s_3,s_5\}$, $S_4 = \{s_4\}$, $S_5 = \{s_1,s_2,s_3,s_5\}$

As $S_1 = S_2 = S_3 = S_5$ and $S_4 \neq S_j$ for i =1, 2, 3, 5, we get the two clusters: $\{s_1,s_2,s_3,s_5\},\{s_4\}$. This denote that the user, who is visiting the hyperlinks as in s_1, may also visit the hyperlinks present in the sessions s_2, s_3 *and* s_5.

7. Conclusion

Fuzzy Set theory assigns to each object a degree of belongingness (membership) to represent an imprecise/vague concept. The focus of rough set theory is on the ambiguity caused by limited discernibility of objects (lower and upper approximation of concept). Rough sets and Fuzzy sets can be integrated: to develop a model of uncertainty stronger than either. In this paper we have presented soft computing on Web mining by using ICA for feature selection and Rough Fuzzy to handle clustering web user sessions. ICA is the algorithm attempts to maximize the independence among extracted features as well as the mutual information between extracted features and a target variable. This algorithm also delivers a classification model that can be used to classify future web users. A rough fuzzy set comes from the combination of two models of uncertainty like vagueness by handling rough sets and fuzzy sets. Rough sets embody the idea of indiscernibility between objects in a set, while fuzzy sets model the ill-definition of the boundary of a sub-class of this set. This approach is useful to cluster web usage access patterns in web log.

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