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A Study of the Factors Influencing Forest Farmers Information Technology Adoption

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Abstract

Information technology is one of the most important factors that have been impacting the development of forestry construction, with forest farmers playing an increasingly crucialrole in promotion of information technology. Survey data in this paper, collected from Yongan County and Youxi County in Fujian Province, usescombinedRough Set Theory (RST) andSupport Vector Machine (SVM), applied for reduction of influential factors of information technology adoption behavior of forestry farmers. The result shows factors, i.e.age, education, highest degree of the family, average annual income, forestland area, average annual income of forestland, status of fixed phone, average spending on mobile phone per month, status of cable TV and connection to the Internet, are of key influential in forestry farmers' decision of information technology adoption.

Keyword*:Influential factors; information technology adoption; rough set theory; support vector machine*

1. Introduction

Information technology plays an important role in the development of agriculture and forestry. In recent years, it has been applied in the studyof agriculture and forestry. But there are still some problems in the promotion of information technology. While the development of agriculture information system is so fast since information technology has been widely used in the assessment of agriculture, research of forestry information system is far behind the agriculture information system.

Adoption of technology innovations in agriculture has attracted considerable attention among development economists [1]. In one research project, some researchers studied the agriculture information system of Durban and found that converging trends in climate change, populationgrowth, and use of resources threaten global food security and environmental sustainability [2]. Some researchers aim to develop a structural model of the barriers to implement green supply chain in Indian automobile industry [3].Other researches use the revised wind erosion equation and geographic information systems to estimate potential wind erosion of agricultural lands in northern China with the conclusions that Shrub barriers reduced wind erosion effectively, but irrigation twice per year could not reduce the wind erosion level markedly in the APEC [4]. Some other researchers incorporate spot4 Data and GIS to study the land cover map delineation of North Sinai, Egypt [5].

While most of these studies focused on farmers engaged in agricultural production, far fewer researches were conducted to benefit forest growers involved in forestry production process.

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In order to accelerate the promotion of information technology in the forestry, it is necessary to study the influential factors of forest farmers' information technology adoption behavior. The study of agriculture information system is often concentrated in the geographical distribution of agriculture [6-8], the behavior of farmers in agriculture production [7-8], and etc., while the study of forestry information system should consider not only those factors mentioned above, but also the particularity of forestry. Forestry has relatively longer cycle and higher risk comparing with agriculture. Considering these features, it is necessary to apply information technology in forestry. Besides, forestry also has more complex distribution system and, oftentimes, more centralized geographic spread, i.e. mountainous regions and less developed Internet networks, so that text messages may be a better way to offer information technology to forest farmers than other channels. Thus, in this paper, we mainly studied text messages adoption of mobile phone which could be applied in the field of forest information system.

2. Forestry Research Status

Compared with the study of agriculture information technology, the study of forestry information technology adoption should takeforestry science and technology, market price, management policy and formal life into consideration. In this paper, forestry science and technology and management policy are mainly analyzed, including seeds' information, silviculture, pest and disease control, forest harvesting, quality standard of forestry product, forest product processing technology, etc. And management policy contains forest rights transfer policy, forest insurance policy, mortgage policy, logging license management, preferential tax policies, and etc.

Throughout its history, the Information System (IS) discipline has engaged in extensive self-examination, particularly with regard to its apparent diversity [9]. Such as in the field of logistics [10], pricing [11] and consumers' cognitive [12]. But in the field of forestry, IS has been rarely applied.In the previous stages of this research, we have studied the forest information technology adoption behavior about hotline and Internet [13].Commoninfluential factors analysis methodsare statistical approach based, such as clustering analysis [14] and logistic model [15]. This paper applied RST and SVM to analyze the affect factors of forest information technology adoption, since, in previous known studies, some researchers has proved that rough set-based mathematic tool can help to improve the classify efficiency of support vector machine [16], other researchers has already used these method to solve ECa (apparent soil electrical conductivity) problems [17].

Forestry regions are mostly distributed in remote areas with highly limitedtraffic and communication, where information is spread orally most of the times, and onlyobvious and ongoing problems matter. When outstanding forestry difficulties occur, with no historical reference and protocol,or suggestion from the experienced farmers, real-time information channel has no way tobe seamlessly accessed as a backup source of information which may save the forest from catastrophic outcome.

In modern society, with abundant information channels, information technology generates comprehensive popularization from urban to rural area.As a real-time and custom designed way to solve forest problems, mobile phone messages has become our channel of study forest farmers' information technology adoption behavior. According to our investigation, almost every forestry farmer has a mobile phone and knows how to send and receive messages. So, it is necessary to know what are the main factors that affecting their adoption behavior. In this paper, using data generated from the investigation held onsite, we not only deeply analyze the factors that influence the forest famers' information adoption behavior, but also provide first hand references to the information broadcasting strategies and policies.

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3. Methodology

This research of influential factors of forest farmers' information technology adoption is based on combined RST and SVM methods.These two methodologiesare increasingly applied and noted in the study of information system and some other fields. Some researchers has applied RST in the study of grey information system, and discussed the properties of the proposed approximation operators in detail [18]. And SVM was usually used in the classification model, *i.e.*, the classification of plant leaf disease recognition [19].

In computer science, a rough set, first introducedby a Polish computer scientist Zdzisław I. Pawlak [20], is a formal approximation of a crisp set (i.e., conventional set) in terms of a pair of sets which give the lower and the upper approximation of the original set. In the standard version of RST, the lower- and upper-approximation sets are crisp sets, but in other variations, the approximating sets may be fuzzy sets.

Let $I=(U,A)$ be an information system (attribute-value system), where U is a non-empty set of finite objects (the universe) and A is a non-empty, finite set of attributes such that $a:U \rightarrow Va$ for every $a \in A$. Va is the set of values that attribute a may take. The information table assigns a value $a(x)$ from Va to each attribute a and object x in the universe U .

With any $P \subseteq A$ there is an associatedequivalence relation $IND(P)$:

$$IND(P)=\{(x,y)\in U^2 \mid \forall a\in P, a(x)=a(y)\}$$

The relation $IND(P)$ is called a P indiscernibility relation. The partition of U is a family of all equivalence classes of $IND(P)$ and is denoted by $U/IND(P)$ (or U/P).

If $(x,y)\in IND(P)$, then x and y areindiscernible(or indistinguishable) by attributes from P .

SVM holds the capability of generating more accurate predictiveratio than lots of statistical and intelligent models in the area ofBFP, and could be used in problems of classification and regression.

Two basic principles of SVM are to firstly map raw data into a highdimensional space using kernel functions and then construct theoptimal separating hyper plane just on the base of support vectors.

For binary classification problem, SVM model is to separate the twoclasses as much as possible. For more detailed information aboutSVM, please refer to researches of Vapnik [21]. The basic principleof SVM can be illustrated as Figure 1.

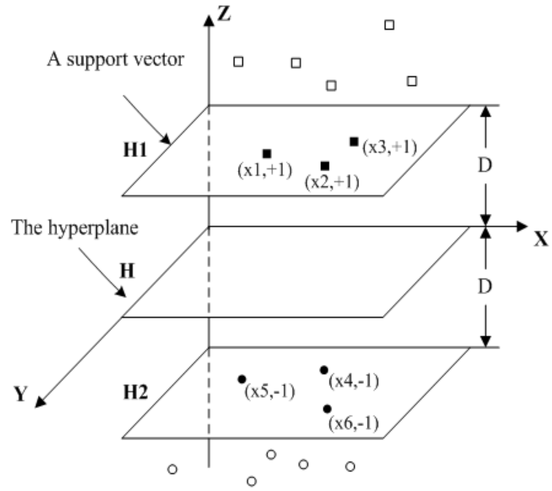

Figure 1. The principles of SVM

Assume m samples be expressed as (x1, y1), (x2, y2), … , (xm, ym), where $x_i \in R^d$ expresses a vector in a d dimensional feature space.For binary classification of BFP, the class label $y_i \in \{-1.+1\}$. xi ismapped into a higher dimensional space, expressed as $\wp$: $R^d \to H^f$, where $f > d$. Thus, the kernel function can be calculated by $K(x_i, x_j) = \wp(x_i)^T \cdot \wp(xj)$. The commonly defined kernel functions in SVMare presented as follows

$$K_{linear}(x_i, x_j) = x_i^T \cdot xj \quad , \tag{1}$$

$$K_{polynomial}(x_i, x_j) = (x_i^T \cdot xj + 1)p \quad , \tag{2}$$

$$K_{gaussian}(x_i, x_j) = \exp(v \| x_i - xj \|^2) \tag{3}$$

$$K_{sigmoid}(x_i, x_j) = \tanh(v x_i^T \cdot xj + \partial) \tag{4}$$

SVMs with linear kernel, polynomial kernel, RBF kernel, and sigmoid kernel are respectively called linear SVM (LSVM), polynomial SVM (PSVM), Gaussian SVM (GSVM), and sigmoidSVM (SSVM).

In this research, we combined RST and SVM to solve the information technology adoption problem. And this is the first time to apply this combination methodology to find the influential factors of forest farmers information technology adoption behavior. First, we could use RST to find out the influential factors that effecting the forest farmers' information technology adoption behavior, and then we could validate the previous study result through SVM algorithm.

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4. Data Analysis

4.1 Variable selection

Applied data was collected by questionnaire conducted in Yongan and Youxi County, Sanming, Fujian Province, including six small villages (Dahu, Hongtian, Xiyang, Banmian, Xicheng and Xiwei). Fujian province is one of the provinces with most extensive forest area in China, with the forestry output value reached 23.37 billion RMB in 2011 [22]. These features makes Fujian province an ideal platform for researchers whose research area is forestry. The questionnaire consists of three parts, with the first part of the basic information of forestry farmers, the second part mainly about forestry farmers' information needs, and the third part about E-commerce of forestry. This paper is mainly focused on the data from the first two parts. We selected several variables from these two parts and used the combination algorithm to classify forestry farmers. Non-probability sampling helps gaining primary data about forest information. We received 177 valid questionnaires except 14 families give incomplete or incorrect information and 5 forest landowners, accounting for 95.2% of all the questionnaires received. The questions in questionnaire have a wide range, including the forestry farmers' basic information, their information needs and requirement, as well as the electronic commerce.

In this paper, in order to get better results that influence the forest farmers' information technology adoption behavior, we selected fifteen variables about forestry farmers: sex, age, education, highest degree of the family, education degree of the householder, average annual income, forestland area, average annual income of forestland, status of fixed phone, ownership of a mobile phone,average spending on mobile phone per month, ownership of a TV, status of cable TV, connection to the Internet and status of subscribing newspapers/magazines. Statistical analysis was generated from the 177 valid data.

4.2 Building information system

A forest information service information system was built by using the huge amounts of data we collected. The system included 177 samples. C means condition attributes, and the C was composed of C1, C2, C3…C15. Detailed information of conditional attributes is shown in Table 1. D means decision attributes, as in this paper is whether the forest farmers are willing to adopt the forest information service. We classified the usage of information technology into three categories: the first category was the forest farmers are willing to adopt the information service, the second category was the forest farmers are not willing to adopt the information service and the third category was the forest farmers are not sure about their preference to adopt the information service. The value of each category was d1=1, d2=2,d3=3. Thus, the whole information system could be shown as follows:

C=(C1, C2, C3 … C15)
D=(d1,d2,d3)
A={C1,C2,C3…C15, d1,d2,d3}

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Table 1. Conditional attribute

Variables	The definition of variables
C1	Sex
C2	Age
C3	Education
C4	Highest degree of the family
C5	Education degree of householder
C6	Average annual income
C7	Forestland area
C8	Average annual income of forestland
C9	Status of fixed phone
C10	Ownership of a mobile phone
C11	Average spending on mobile phone per month
C12	Ownership of a TV
C13	Status of cable TV
C14	Connection to the Internet
C15	Status of subscribing newspapers/magazines

4.3 Data completion

In practice, most of the information collected by the researchers is oftentimes incomplete and defect. We usually named the information system which involved incomplete or defect information as incomplete information system. If simply eliminate the sample with incomplete information, outcome would suffer from wasting large amount of data resources and losing information that hide in the incomplete data. Because the forest information service information system of this paper was an incomplete information system, proper approachwould be completing the defect data. To make this modification, this paper applied Conditioned mean Completer as the complete algorithm. This method substitutes missing values for numerical attributes with mean value of the mean and mode values which are conditioned to the same decision classes. The detailed calculation stepsare shown in the Table 2.

Table 2. Incomplete information system

U(forest farmers)	Conditional attributes C7	Conditional attributes C8	Decision attributes D
X1	12	5000	1
X2	13	f2=(6000+6800)/2=6400	2
X3	f1=(13+22)/2=17.5	6000	2
X4	21	7500	1
X5	19	f3=(5000+7500)/2=6250	1
X6	22	6800	2

Ps：the initial value of f1, f2, f3 is null

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4.4 Data discretization

This paper adopted Equal Frequency binning method to discretize the five continuous variables. This method classified the domain of the continuous variables into K small partitions. Every partition is a Bin, with every Bin has the same amount of samples, and the repeat value belongs to a same Bin. The final discretization results were stated in the Table 3.

Table 3. Discretization results

Assessment indicators	Attributes	Discretization interval
Age	C2	$[0,44)$ $[44,51)$ $[51,\infty)$
Average annual income	C6	$[0,24500)$ $[24500,49000)$ $[49000,\infty)$
Forestland area	C7	$[0,15)$ $[15,51)$ $[51,\infty)$
		$[0,14)$ $[14,51)$ $[51,\infty)$
Average income of forestland	C8	$[0,4500)$ $[4500,19123)$ $[19123,\infty)$
		$[0,5250)$ $[5250,22698)$ $[22698,\infty)$
Average spending on	C11	$[0,48)$ $[48,73)$ $[73,\infty)$
mobile phone per month mobile		$[0,48)$ $[48,78)$ $[78,\infty)$

4.5 Data reduction and results

In the data mining process, we called the conditional attributes that didn't supply any useful information as redundant attributes. Reduction of attributes means under the condition of keeping knowledge classification ability remain the same level, and obviously, reducing redundant attributes as much as possible would generate statistics that better describe the reality. At the end of the day, we can get a reduction information system. The methodology we applied in the research is Johnson Algorithm of Rosetta software. The final reduction result were been illustrate in the Table 4.

Table 4. Reduction results

Reduction results
{ age, education, highest degree of the family, average annual income, forestland area, average annual income of forestland, status of fixed phone, average spending on mobile phone per month, status of cable TV, connection to the Internet }

5. Validation of the data

I. Using the data we collected from the investigation, we could get the training samples of forest farmers which could be illustrated as (x_i, y_i).And x_i means the i forest farmer's assessment indicator information. y_i means the forest farmer's adoption situation, $y_i = 1$ means the forest farmer is willing to adopt the forest information service, $y_i = 2$ means the forest farmer is not willing to adopt the forest information service and $y_i = 3$ means the forest farmer is not sure whether he/she would like to adopt the forest information service or not.

II. Constructing the optimal separating hyper plane just on the base of support vectors depend on the training samples of Step I.

$$f(x) = sign\left\{\sum_{i=1}^{n} a_i y_i (x_i \cdot x) + b\right\};$$

III. Take advantage of the optimal separating hyper plane to classify the forest farmers' information technology adoption behavior.

$y = sign\left\{\sum_{i=1}^{n} a_i y_i (x_i \cdot x) + b\right\} = +1$ (the forest farmer adopt the service),

$y = sign\left\{\sum_{i=1}^{n} a_i y_i (x_i \cdot x) + b\right\} = -1$ (the forest farmer do not adopt the service),

$y = sign\left\{\sum_{i=1}^{n} a_i y_i (x_i \cdot x) + b\right\} = 0$ (the forest farmer do not sure whether to adopt the service);

IV. Comparing the training set and predicting set, we find that none of the sample was been wrong predicted, thus the diagnostic accuracy is 100%. Which means the information system we built is well structured. And what's more, the combination of RST and SVM to predict the influential factors could avoid the data selection blindness which is depending on the experience of the normal SVM. It's not only very practical and also well improved the prediction speed and accuracy.

6. Summary and Conclusions

Rooted in extensive and evolutionary effort in information system researches and studies, this paper, which specifically focused on information technology adoption influential factors of forest farmers, is well supported theoreticallyand practically. The analysis shows that age, education, highest degree of the family, average annual income, forestland area, average annual income of forestland, status of fixed phone, average spending on mobile phone per month, status of cable TV and connection to the Internet are the key factors impacting forestry farmers' decision of information technology adoption.

The reason why the age of the forest farmer could affect his/her adoption is that, as a new technology service, the younger the target populationis, the easier he/she will accept the new information. Education and the highest degree of the family indicatetheimportanceof new knowledge in this family's regard. Average annual income, forestland area and average annual income of forestland express the financial status of the family, andindirectly reveal the affordability of forest information to the family. Status of fixed phone, status of cable TV and connection to the Internet reflected the family's interests and acceptance to the new technology. And average spending on mobile phone had indirectly expressed how much the family is willing to pay forrelevantinformation.

The reduced factors include sex, education degree of the householder, ownership of mobile phones, ownership of a TV and status of subscribing newspapers. All of the above factors are very important attributes of forest farmers, but they couldn't affect the classification result. In

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particularly, sex is not the key factor affecting the adopting behavior; education degree of the householder do not mean the education degree of the respondent, and whether they are willing to adopt the information technology is decided by the respondent; since almost everyone has a mobile phone, the ownership of mobile phones can't decide the adoption behavior, either; and unlike the former attribute, why the status of subscribing newspapers has been deduced is because almost all of the families don't subscribe newspapers.

Every attributes has their own importance, some of the attributes are key factors while some other attributes are just important factors. Key factors can impact the classification results, while important factors can't. Those important factors are called redundant data, and when we have successfully reduced the data redundancy, the result could be very useful to the government and corporation while they promote new forest information.

In summary, we did not only deeply analyze the factors that influence the forest famers' information adoption behavior, but also provide first hand references to the government and corporation.Here are some suggestions for relevant departments. In one hand, government or corporation could choose the regions where the forest farmers have relatively higher income and better financial situations as their target place. In fact, the popularity of information technology would help improve the income level of local farmers. Thus, the promotion of forest information technology and improvement of forest farmers' income level can realize a virtuous cycle.

In the other hand, according to the analyze results, younger people and better education background families are more willing to adopt information technology. And families who are highly interested in new technology will be much easier to accept the promotion of forest information technology. Thus, relevant department might help the farmers improve their knowledge about information technology through publicity the importance of information technology in forestry. In turn, the publicity of information technology would expand the scope of the information technology adoption audience.

In the future, before the government and corporation promote some forest information technology, they might study the status of those key factors about the local forest farmers first. And then they could decide whether to promote information technology depending on the investigation results. Thus, the study can help the departments reduce the unnecessary cost of waste.

Do to the limit scope of the survey; we still can't do general study on the influential factors of information technology adoption of national forest farmers. For the sake of completeness, our research will carry on, and we hope to figure out the whole status of forest farmers of our country.

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