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RELIABLE PAYMENT GATEWAY COMPONENT SELECTION USING FUZZY AND PRISM CLASSIFIERS

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ABSTRACT

A Payment gateway is a web service used in e-commerce for settling money transactions and a number of service providers offering the web-service-payment-gateway in the market. Payment gateway offers a secured way of trading with a simple interface, high reliability and flexibility, Easy to use and integrate with the merchant's ecommerce web application. Fair selection among the web services are appreciated for mounting to the API's. Reliability is needed for selecting a good web service component. In the entry level we introduced eight new metrics for analysing payment-gateway-web-service-components. PRISM and Fuzzy classifications techniques are applied in the dataset for web service components. In the Fuzzy classification thirty two intricate attributes are considered for analysis. For identifying the reliable component between entry level class and fuzzy classifications, gauging is done using linear mapping and the purity level of the attributes of the web service is measured via Theil indexing.

Keywords: prism algorithm, fuzzy classification, linear mapping, theil indexing.

INTRODUCTION

In web service components, identifying the reliable component is a great task. Budget which is an entry level assessment and Actual is obtained after applying the corresponding methodology. Linear mapping architecture is employed here to select a good component referred in Figure-1. Budget is our entry level assessment and the same will be verified by the methodology Fuzzy classification. Here PRISM classification is employed to generate plenty number of rules, so as to provide an answer for the incoming patterns. Analysing and comparing the multiple methodologies results will provide good idea to choose between components. Six neural network based classifiers is taken for evaluation based on recognition accuracy. For comparison purposes k-nearest neighbour classifier and naive Bayes classifier are employed and it is found that the tree structured and Naïve Bayes outperforms than others [1]. In this paper identifying a reliable web service payment gateway component is the total motivation. In order to make mobile payment as a flexible payment one paper proposes mobile web services concept framework solution [27]. Here Dataset is considered for web service and newer attributes that are ever used in the research articles for the past one decade. We have taken 40 new attributes of different cases and issues in analysing the web services. Class analysis is done through pre-processing the dataset and same is used for classification purpose. The entry level analysis results are checked and corrected with Fuzzy classification using linear mapping. The results obtained through Budget and actual are common and thus making us to identify the more reliable web service component. This type of prediction and identification is a newer technique ever available so for in the articles. Large number of attributes and web services are the ever green phenomena in the field of selection of web service. Various ways are present for analysing the best component. Semantic model and distance measure is also used for analysing the best web service components and high performance is achieved thus resulting in precise accuracy [22]. Payment options, Payment Features and Payment Price are the three other intricate phenomena taken for identifying the right component. Fair selection also emphasis user's preferences and choices to select a particular component. QAR based filtering scheme is used for the selection of best web service components. The recommendations done here outperforms by bringing the accuracy [21]. In the above said thirty two innovative metrics are considered for gauging the reliable component using the Fuzzy Classification. While evaluating the payment web service component Options, Features and Prices provide a clear picture about the web service component for errorless selection. We have taken twenty eight papers for our analysis and various Quality of service such as accuracy, robustness, flexibility and efficiency is achieved by following various methodologies like Genetic algorithms, KNN, Bayes, Fuzzy cluster and Neuro fuzzy cluster. In this paper we have followed a hybrid technique by applying both PRISM algorithm and Fuzzy classification and Reliability is the quality of service that has been achieved by us. A survey focuses in investigating various problems and the deploying directions are managed by the Web Service Management Systems and at last some of the key features are identified [23]. The functionalities and principles of PRAMID-S are presented and peer to peer topology is used to organize web service registries [24]. In order to bring the flexible compensation options they bought an environment to deal with advanced compensations and contract based approach is used [25]. Goal oriented business oriented approach is used which is capable of responding to the change in circumstances [26]. Third party system must be more reliable and in order to increase its standard a new scheme BulaPay is introduced [28]. In the coming sections we will see the Literature study and core technical comparisons, Proposed methodology, Theil indexing, Results and discussions,

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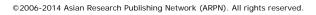
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Observations and Technology ideology of the paper, conclusions and References.

Literature study and core technical comparisons

l able 1 Literature comparison

Literature			Cluster		Classi	fication	Hybrid/ Association
		Fuzzy Cluster	Neuro Fuzzy Cluster	KNN Cluster	FNN	Bayes	
Lam et al. [2014]	×	x	x	~	x	·	
Shen et al. [2008]	×	×	×	×	×	×	SOINN
Chiang et al. [2014]	×	×	×	×	✓	×	
Cetisil et al. [2010]	×	×	✓	×	×	×	
Chaterjee et al. [2014]	×	✓	×	×	×	×	
Azar et al. [2013]	×	×	×	×	x	×	Hard and tuzzy algorithms
Pal et al. [2012]	×	✓	×	×	x	×	
Mungle et al. [2013]	✓	✓	×	×	×	×	
Mei et al.[2011]	×	×	×	×	×	×	Fuzzy clustering with multi medoids
Ishibuchi et al. [2014]	×	×	×	×	×	×	Repeated double cross validation
Saha et al. [2014]	×		×	×	×	×	
Hudec et al. [2012]	✓	×	×	×	x	×	
Ciha et al. [2014]	×		×	×	×	×	
Bakirh et al. [2011]	✓	×	×	×	×	×	
Ayse et al. [2011]	✓	×	×	×	×	×	
Lavine et al. [2009]	✓	×	×	×	×	×	
Aydogan et al. [2012]	×	×	×	×	×	×	Genetic Integer programming
Orkcu et al. [2011]	×	×	×	×	×	×	Neural networks with Genetic Algorithm
Jabbar et al. [2013]	✓	×	×	V	×	×	
∠hang et al. [2014]	×	✓	×	×	×	×	
Iyagı et al.[2012]	×	×	×	×	×	×	QAH Based filtering scheme
Yue et al. [2009]	×	×	×	×	×	×	Semantic model and distance measure
Yu et al. [2008]	×	×	×	×	×	×	Web service management system
Pilioura et al. [2009]	×	×	×	×	×	×	Hybrid peer to peer topology
Schafer et al. [2008]	×	×	×	×	×	×	Contract based approach
Choudry et al. [2010]	x	×	×	×	×	×	Goal Uriented Co-ordination
Chong et al. [2006]	×	x	x	×	×	×	Framework solution in web services
Liang et al. [2009]	×	×	×	×	×	×	BulaPay-A New Scheme
Our paper	×	×	×	×	×	×	Prism Algorithm and Fuzzy Classification





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		Clus	ster		Classif	ication		
Literature	Genetic Cluster	Fuzzy Cluster	Neuro Fuzzy Cluster	KNN	Cluster FNN	Bayes	- Hybrid	QoS
Lam et al. [2014]	×	×	×	Optimal Clusters	×	Makes one supervised result	x Reduced error rate	Robustness
Shen et al. [2008]	×	×	×	. x	× Produces	×	With high probabilistic Value	Speed
Chiang et al. [2014]	×	×	x Good	*	Accurate results	*	×	Accuracy- 90%
Cetisil et al. [2010]	×	x Prediction	recognition rate	1 x	×	×	×	Reliability
Chaterjee et al. [2014]	×	Possibility Is high	×	*	*	×	Minimum number of	Efficiency
Azar et al. [2013]	*	x Threshold is	×	×	×	×	Clusters provides maximum Information	n Accuracy
Pal et al. [2012]	*	Obtained in a Cluster	*	×	×	×	×	Consistency
Mungie et al. [2013]	Solves inconsiste	ency ×	*	×	×	*	×	Pareto Front
Mei et al.[2011]	×	×	*	×	×	×	achieves more number of ingredients in qos	Robustness
Ishibuchi et al. [2014]	×	×	×	×	×	×	Acting on n number Of heuristics	Evaluation
Saha et al. [2014]	x Gives	Removes conflictness	×	×	*	×	Optimal solution	Evaluation
Hudec et al. [2012]	general ideology	×	×	×	×	×	×	Fusion
Ciha et al. [2014]	×	Improves cohesion	×	*	×	×	×	Fatness
Bakirh et al. [2011]	Gives general ideolog		×	×	×	×	×	Flourishment
Avse et al. [2011]	Accura Results Reduce	×	×	×	×	*	×	Accuracy-95%
Lavine et al. [2009]	searchi Time	ng ×	×	×	×	×	Integration of PCA In fitness function	Efficiency
Audocon of [2012]	×	×	×	×	×	×	Sufficient number clusters provide Greater efficacy	of Precise Accurac
Aydogan al.[2012] Orkcu et al.[2011]	*	*	×	×	×	×	Improves cohesion	Efficiency

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Jabbar et al. [2013]	Ambiguity will Be removed	l *	*	×	*	×	×	Accuracy
Zhang et al. [2014]	×		pership	×	×	×	x New	Effectiveness
	x x		×	×	×	×	recommendatile	antness
Tyagi et al. [2012]	×	×	×	×	×	*	outperforms	Accuracy
							High Precision	
Yue et al. [2009]	×	×	×	×	×	×	Is achieved	Precise Accuracy
Yu et al. [2008]	×	×	×	×	×	×	×	Interoperability
Pilioura et al. [2009]	×	×	×	×	×	*	×	Availability
Schafer et al. [2008]	×	×	×	*	×	×	×	Feasibility
Choudry et al. [2010]	×	×	×	×	×	×	×	Availability
Chong et al. [2006]	×	×	×	×	×	×	*	Flexibility
Liang et al. [2009]	×	×	×	×	×	×	×	Flexibility
Our paper	×	×	×	*	×	×	*	Reliability

On explaining the findings of the above studies, among twenty eight papers we have three categories. They are cluster, classification and hybrid/association. Under cluster we have genetic cluster, fuzzy cluster, KNN cluster and Neuro Fuzzy cluster. Bayes lies below the category of Classification. If two domains combine for a particular application we call them as hybrid. If association rule is formed based on the web service then it will come under the category of association. Six papers used genetic cluster which follows the principle of cross over and mutation and helps in solving inconsistency thereby providing a general ideology. In certain cases it reduces searching time and ambiguity and provides accurate results. Pareto front, Fusion, Integration, Flourishment and Accuracy are the QoS achieved as a result of genetic cluster (Mungle et al, 2013), (Hudec et al, 2012) (Bakirh et al, 2014) (Arse et al., 2011) (Lavine et al., 2009) (Jabber et al, 2013). Fuzzy is applied if uncertainty prevails, and it follows the procedure of membership functions and its membership utilization is high. In certain cases threshold is obtained in a cluster thereby removing conflict. Thus due to obtaining of a threshold value the possibility of predicting a particular one goes higher. Threshold also plays a vital role in cluster formations. In one paper it improves cohesion. It provides QoS such as Efficiency, Accuracy, Consistency and Complexity (Chaterjee et al, 2014) (Pal et al., 2012) (Mungle et al., 2013) (Saha et al., 2014) (Ciha et al, 2014) (Zhog et al., 2014). Neuro Fuzzy classifier is used to improve the distinguish ability rate of certain overlapped classes. One paper uses neuro fuzzy classifier thereby achieving reliability as its QoS.KNN is a classifier and Bayes is a Classification. One paper uses both KNN and Bayes and as a result optimal number of clusters are found due to KNN and supervised result is obtained due to Bayes (Lam et al, 2014) (Jabber et al, 2013). KNN and Bayes in combination provide Robustness as its OoS.FNN focuses on Accuracy. One paper uses Fuzzy Neural Network to provide accurate results (Chiang et al. 2014). Thus it helps in achieving accuracy of 90% as its QoS. papers come under the category Hybrid/Association. Through the concept of hybrid, error rate is reduced and as a result the speed is increased. On focusing about the clusters, minimum number of clusters provides maximum information. And in addition sufficient numbers of clusters provide Efficacy. In some cases new recommendation has been formulated and it outperforms the previously existing one. In general it acts on n number of heuristics and high precision is achieved as a result.

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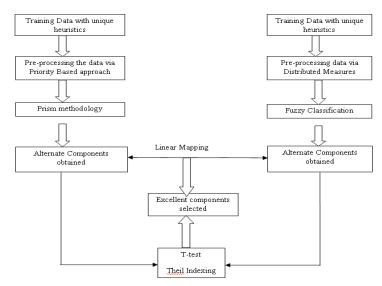


Figure-1. Linear mapping architectural view for web service components selection.

In the above said architecture for the payment gateway web services, we have considered two types of different set of heuristics and are measured and analyzed via unique mapping methodology for the web service component selection. The result produces supreme component for the API applications. The heuristics are gauging through Theil indexing methodology.

Table-3. Data set.

Legend-1: SSLE- Secure Socket Layer Encryption, FD-Fraud Detection, MS- Modes Supported, CS-Cloud Support, PE-Password Encryption, CSS- Certified Security Standards and API- Application Program Interface.

Web Service				Heuristics					
Component				Heurisucs					
Web service	SSLE	FD	MS	Analytics	CS	PE	CSS	API	Class
CCAVENUE	128	HD	Credit	Report	NO	NO	PD2	PAJ	Fair
CCAVENUE	128	HD	Credit	Summary	NO	NO	PD2	PAJ	Fair
CCAVENUE	128	HD	Credit	ShareRep	NO	NO	PD2	PAJ	Good
CCAVENUE	128	HD	Debit	Report	NO	NO	PD2	PAJ	Fair
CCAVENUE	128	HD	Debit	Summary	NO	NO	PD2	PAJ	Fair
CCAVENUE	128	HD	Debit	ShareRep	NO	NO	PD2	PAJ	Good
CCAVENUE	128	HD	NB	Report	NO	NO	PD2	PAJ	Fair
CCAVENUE	128	HD	NB	Summary	NO	NO	PD2	PAJ	Satisfactory
CCAVENUE	128	HD	NB	ShareRep	NO	NO	PD2	PAJ	Fair
CCAVENUE	128	HD	Mobile	Report	NO	NO	PD2	PAJ	Satisfactory
CCAVENUE	128	HD	Mobile	Summary	NO	NO	PD2	PAJ	Satisfactory
CCAVENUE	128	HD	Mobile	ShareRep	NO	NO	PD2	PAJ	Fair
EBS	256	FP	Credit	Payment Trend	Yes	S	PD2	PAJ	Excellent
EBS	256	FP	Credit	ShareRep	Yes	S	PD2	SC	Excellent
EBS	256	Geo	Credit	Payment Trend	Yes	S	PD2	PAJ	Excellent
EBS	256	Geo	Credit	ShareRep	Yes	S	PD2	SC	Excellent
EBS	256	PD	Credit	Payment Trend	Yes	S	PD2	PAJ	Good
EBS	256	PD	Credit	ShareRep	Yes	S	PD2	PAJ	Excellent
EBS	256	M	Credit	Payment Trend	Yes	S	PD2	PAJ	Good
EBS	256	M	Credit	ShareRep	Yes	S	PD2	SC	Excellent

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Proposed methodology

Data set

The Dataset are formed for analysing the payment gateway web services and for identifying its reliability through different attributes. Each and every attribute has got its own significance to gauge a particular web service. Every acronym of the attribute is explained throughout the legend. Identifying the class is the first and the fore most goals for classification purpose.

There are still plenty number of payment gateway web services available in the existing online marketing like Pay Zippy, Pay U, Direct Pay etc. Those web services will also have such a type of above attributes and these services come under the category of satisfactory class. For the simplification of the training set that satisfactory class web services are not mentioned above.

Apply prism algorithm to generate rules

There are various clusters like genetic cluster, fuzzy cluster, fuzzy neuro cluster, KNN cluster and FNN cluster. Fuzzy clustering based genetic algorithm solves conflict objectives and is capable of generating good pareto front [8]. Extension of logical function was created and this paper provides the overall ideology and fusion [12] repeated double cross validation also provides the

generalization ability of the classifier [10]. Fuzzy bi criteria optimization model is formulated and it maximizes the intra modular coupling density and functionality [13].

In one paper new incremental genetic algorithms was proposed and it decreases the construction time for a data set. In general genetic algorithm reduces the searching time when PCA is embedded into the fitness function [16]. Prism Classifier is rule based classifier that largely reduces the data set into rules and coverage based algorithm. It gives the most accurate rules for each class. In order identify class in non numerical data set priority based distributed measure can play vital role to form classes. Genetic algorithm based automatic web page classification system used HTML tags and classification accuracy is higher [15]. In addition to this a heuristic approach based on genetic algorithm was proposed to discover accurate and short classification rules [17]. On having a comparison between back propagation and genetic algorithms, it is found that both are efficient for the classification problems [18]. KNN combines with genetic algorithm in providing accurate treatment for heart disease [19] while fuzzy and hard clustering algorithms are used for the treatment of thyroid diseases [6]. Attributes are prioritized and weighted to its maximum value as 100 and then decrease with a constant to assign it to next ranked instance of attribute.

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Table-4. Priority based distributed measure.

Legend-2. SSL- Secure Socket Layer, FD-Fraud Detection, MS- Modes Supported, CS-Cloud Support, PE-Password Encryption, CSS- Certified Security Standards and API- Application Program Interface

Web service	Heuristics				
Components					

	SSL	FD	MS	Analytics	CS	PE	CSS	API	Grand total	%	Class
CCAVENUE	50	77.78	100	50.2	50	75	100	33.33	536.31	74.83	Fair
CCAVENUE	50	77.78	100	33.6	50	75	100	33.33	519.71	72.52	Fair
CCAVENUE	50	77.78	100	100	50	75	100	33.33	586.11	81.78	Good
CCAVENUE	50	77.78	87.5	50.2	50	75	100	33.33	523.81	73.09	Fair
CCAVENUE	50	77.78	87.5	33.6	50	75	100	33.33	507.21	70.77	Fair
CCAVENUE	50	77.78	87.5	100	50	75	100	33.33	573.61	80.04	Good
CCAVENUE	50	77.78	75	50.2	50	75	100	33.33	511.31	71.35	Fair
CCAVENUE	50	77.78	75	33.6	50	75	100	33.33	494.71	69.03	Satisfactory
CCAVENUE	50	77.78	75	100	50	75	100	33.33	561.11	78.3	Fair
CCAVENUE	50	77.78	62.5	50.2	50	75	100	33.33	498.81	69.6	Satisfactory
CCAVENUE	50	77.78	62.5	33.6	50	75	100	33.33	482.21	67.29	Satisfactory
CCAVENUE	50	77.78	62.5	100	50	75	100	33.33	548.61	76.55	Fair
EBS	100	100	100	83.4	100	50	100	33.33	666.73	93.03	Excellent
EBS	100	100	100	100	100	50	100	66.66	716.66	100	Excellent
EBS	100	88.89	100	83.4	100	50	100	33.33	655.62	91.48	Excellent
EBS	100	88.89	100	100	100	50	100	66.66	705.55	98.45	Excellent
EBS	100	44.45	100	83.4	100	50	100	33.33	611.18	85.28	Good
EBS	100	44.45	100	100	100	50	100	66.66	661.11	92.25	Excellent
EBS	100	66.67	100	83.4	100	50	100	33.33	633.4	88.38	Good
EBS	100	66.67	100	100	100	50	100	66.66	683.33	95.35	Excellent

Priority based distributed measure has employed in the Table-4. Every attribute has got its own significant quality and weight age according to its application. The highly valuable attribute is prioritized and given highest score of 100. The remaining less prioritized attributes is given score accordingly. This type of measure is helpful to find and identify the correct class. Now Prism Algorithm can be applied on this data set to generate Rules.

Prism algorithm

Accuracy(C) = P(o)/n

Where P (o) is No of Occurrence of an Instance that infers Class C

n is the Total number of occurrence of an instance.

Step-1: Let a1, a2, a3 be the instance of attribute A

Step-2: Let C be the Class

Step-3: Calculate Accuracy for each instance of the attributes

X1 = No of occurrences a1 that infer C/

No of occurrences a1

X2 = No of occurrences a2 that infer C/

No of occurrences a2

X3 = No of occurrences a3 that infer C/

No of occurrences a3

Step-4: Maximum of x1, x2 and x3 will be opted out for rule, if x1 is maximum rule becomes if A = a1 and follows.

Step-5: Skips a2 and a3 instance of attribute A and moves next Attributes and repeat the same for all other attributes with reduced data set

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Table-5. Reduced Data Set.

Legend-3: SSL- Secure Socket Layer, FD-Fraud Detection, MS- Modes Supported, CS-Cloud Support, WE-Wireless Encryption and API- Application Program Interface.

Web service components				Heuristics					
Web service	SSL	FD	MS	Analytics	CS	WE	CS	API	Class
EBS	256	FP	Credit	Payment Trend	Yes	Yes	PD2	PAJ	Excellent
EBS	256	FP	Credit	ShareRep	Yes	Yes	PD2	SC	Excellent
EBS	256	Geo	Credit	Payment Trend	Yes	Yes	PD2	PAJ	Excellent
EBS	256	Geo	Credit	ShareRep	Yes	Yes	PD2	SC	Excellent
EBS	256	PD	Credit	Payment Trend	Yes	Yes	PD2	PAJ	Good
EBS	256	PD	Credit	ShareRep	Yes	Yes	PD2	PAJ	Excellent
EBS	256	M	Credit	Payment Trend	Yes	Yes	PD2	PAJ	Good
EBS	256	M	Credit	ShareRep	Yes	Yes	PD2	SC	Excellent
EBS	256	FP	Debit	Payment Trend	Yes	Yes	PD2	PAJ	Excellent
EBS	256	FP	Debit	ShareRep	Yes	Yes	PD2	SC	Excellent
EBS	256	Geo	Debit	Payment Trend	Yes	Yes	PD2	PAJ	Good
EBS	256	Geo	Debit	ShareRep	Yes	Yes	PD2	SC	Excellent
EBS	256	PD	Debit	Payment Trend	Yes	Yes	PD2	PAJ	Good
EBS	256	PD	Debit	ShareRep	Yes	Yes	PD2	SC	Excellent
EBS	256	M	Debit	Payment Trend	Yes	Yes	PD2	PAJ	Good
EBS	256	M	Debit	ShareRep	Yes	Yes	PD2	SC	Excellent
EBS	256	FP	NB	Payment Trend	Yes	Yes	PD2	PAJ	Good

By applying the PRISM algorithm necessary rules are generated by taking high probabilistic value which is likely to be available as a condition in the rule. Using the obtained conditions it is possible for us to exhibit our recommendation for each and every rule. Once the attribute satisfies this rule then those rows are taken into account and hence we find the reduced dataset. The rules are acting as a ready reconer; from this we can conclude the recommendation for the incoming pattern by revealing the exact class.

Apply fuzzy clustering with rules

Euclidean distance and fuzzy clustering

Fuzzy plays a predominant role in uncertainty and in one paper fuzzy clustering analysis is done by creating a compatibility matrix and the result is the generation of fuzzy equivalent generation. Optimal threshold value is set to obtain software quality [7]. Novel multivariate fuzzy forecasting algorithm is implemented to predict the future occurrences of different web failures thus providing better efficiency and predictive accuracy [5]. Fuzzy clustering with multi-medoids (FMMdd) is done in one paper and rich cluster-based

information is obtained as a result and it is less sensitive to noise [9] and fuzzy clustering is applied to categorical data to solve two conflicting values and optimal solution is obtained as a end point [11]. Fuzzy clustering based on bipartite modularity is done for validating the index by utilizing its own membership property and thus resulting in reliability [20]. SOINN (self-organizing incremental neural network) realizes very fast classification and its speed up ratio is high [2]. Fuzzy neural network (FNN) is applied for cluster assessment system for facial attractiveness and it provides a 90% of accuracy [3]. Since Prism gave most accurate rules and it is necessary to find the gateway services which matches with each classes and this technique clusters more than one web service into a class. Adaptive neuro fuzzy classifier distinguishes rates of overlapped classes and resulting in the better recognition rates [4].

Steps to do fuzzy clustering

Step-1: Allocate numbers for dataset based on the priority of each instance of attributes

Step-2: Let us assume X(x1, y1, z1...) be the values in Rules

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Step-3: Let us assume C(x2, y2, z2...) be the values in data set

Step-4: For each Record C that infers the class which is inferred by X the Distance and Membership value must be calculated.

Step-5: Distance can be identified by the following formula, $dxc1 = |\sqrt{(x^2-x^1)^2 + (y^2-y^1)^2}|$

where x2 -x1 is distance between same attributes say SSL Encryption and y2- y2 is distance between same attributes Fraud Detection

Step-6: Now Calculate dxc1, dxc2... Dxcn

Web Service Components

DirectPay

Step-7: Membership value is the ratio of 1/distance to the sum of reciprocals of distances

Step-8: Membership Value for ci = (1/dxci) / (1/dxct+1/dxc2...+1/dxcn)

Step-9: Calculate all ci values and get associated web services, where ci value is the threshold

Step-10: The threshold is 0.2 for web services that are clustered into a class

Step-11: Similarly the web services clustered into other classes can be identified

Apply fuzzy classifiers on other data sets

In order to rate payment gateway services with high precision, it requires to research about its core attributes. Features, Pricing and Payment Options are some Parameters to be analysed across all Payment Gateway services.

Steps to be followed for fuzzy classifier

Step-1: Apply Priority based distributive measures on each data set and find the percentile for each service.

Step-2: Identify Membership Value for each attributes

Step-3: Membership values can be obtained by prioritizing each attributes that can vary from 0 to 1

Step-4: For each attribute membership value is obtained by percentile measure of each attribute with respect to its prioritized values

Step-5: Fuzzy value for each service is obtained by: Percentile (\sum weight * μ (xi))

Table-6. Payment Options. **Legend-4:** EMI-Equated Monthly Instalment

Heuristics

•						1	•	
Web service	Credit card	Debit Card	Net Banking	Cash Cards	Mobile Payment	MultiBank EMI	Class	Class Number
CCAVENUE	7	73	48	5	2	2	Excellent	5
EBS	6	50	50	5	0	8	Excellent	5
PayZippy	4	73	48	0	0	0	Satisfactory	2
PavII	4	73	33	1	0	4	Satisfactory	2

For the same web service of payment gateway other different core metrics are taken for the

measurements. Here priority has given to the high value metric and identified their classes for the above said.

Satisfactory

Table-7. Payment features.

Web service Components					Heuristics								
Web service	Multi-Currency	Customizable Page	Dynamic Routing	Retry Option	1-click checkout	Storefront	Shopping cart	Mobile Checkout	marketing tool	Phone pay	DynamicEvent Notification	Customer Support	Invoice
CCAVENUE	yes	yes	Yes	yes	yes	yes	yes	yes	yes	yes	yes	24by7	Yes
EBS	yes	yes	Yes	no	no	no	yes	no	yes	no	no	24by7	Yes
PayZippy	no	yes	No	no	yes	no	yes	yes	no	yes	yes	8am to 8pm	No
PayU	yes	yes	Yes	yes	yes	no	yes	yes	no	yes	no	24by7	No
Direcpay	no	yes	No	yes	no	no	yes	yes	yes	yes	yes	24by7	No

New thirteen attributes are taken for measuring and identifying reliable web service component and noted the wroth while among the given web services.

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Table-8. Payment price.

Legend-5: AE-American Express, CTT-Central Transport Training, MC-Master Card, JCB-Japan Credit Bureau, NB-Net Builder, CTT-Charity Technology Trust, DTT- Discovery Telecom, DC- Debit Card.

Web service Components						Heuristics							
Web service	Setup Fee	DTT	CTT	MC	Visa	DCCB	JCB	DC	NB	Paypal	AE	Cash Cards	yearly charge
CCAVENUE	0	0	0	3.5	3.5	3.5	5	1.25	4	0	5	5	1200
CCAVENUE	30000	0	0	2.25	2.5	2.5	3.6	1.25	2.5	0	3.6	3.6	3600
EBS	12000	0	0	4	4	5	5	3	4	2.9	5	0	0
EBS	18000	0	0	3.5	3.5	4.5	4.5	1.75	3.5	2.9	4.5	0	0
EBS	24000	0	0	2.75	2.75	4	4	1.5	2.75	2.9	4	0	0
EBS	30000	0	0	2.5	2.5	3.75	3.75	1.25	2.5	2.9	3.75	0	0
PayZippy	0	<=2000	0	0	0	0	0	0.75	0	0	3.5	0	0
PayZippy	0	>2000	0	0	0	0	0	1	0	0	3.5	0	0
PayZippy	0	0	0 to 5	3.5	3.5	0	0	0	3.5	0	3.5	0	0
PayZippy	0	0	5 to 10	3.25	3.25	0	0	0	3.25	0	3.5	0	0
PayZippy	0	0	10 to 25	3	3	0	0	0	3	0	3.5	0	0
PayZippy	0	0	25to 100	2.5	2.5	0	0	0	2.5	0	3.5	0	0
PayU	6000	<=2000	0	4.9	4.9	4.9	0	0.75	4.9	0	4.9	4.9	0
PayU	6000	>2000	0	4.9	4.9	4.9	0	1	4.9	0	4.9	4.9	0

Table-7 and Table-8 revels some facts about their proficiency in terms with selecting well known and reliable web service components. In India 85% percentage of the merchants preferred only CCAVENUE and EBS for their reliable service. They are all pioneers in the market. 27 various currencies are accepted by that web service components. CCAVENUE and EBS components are very keen in conversion of currencies in a more precise manner so that users will not face any loss in terms with currency conversions. They are acting as a distributed resolution between merchant and a customer. CCAVENUE and EBS is really a merchant centric and are covered under trust pay. 50+ Debit cards and Net banking facilities, 5 credit

cards, 4 cash cards and 2 mobile payments with 100+ options and services are available. Features like phone pay, Invoice payment system, mobile checkout page and 100 million transactions are done by the components with minimum issues in the last financial year. Risk and Fraud Identification system provides a guard for the customers. The above facts reveal their Excellencies. Payment options, Payment features and Payment price is having a great relationship and attributes which is all deployed in the respective Tables 6, 7 and 8 are innovative and novel to prove the reliability of the web service components. Thus web service components like CCAVENUE and EBS are categorized with excellent.

Table-9. Distributed Measures for payment options. **Legend-6:** EMI-Equated Monthly Instalment

Web service components			Heuristics					
Web service	Credit card	Debit card	Net banking	Cash Cards	Mobile payment	Multi bank EMI	Total	%
CCAVENUE	100	100	96	100	100	25	521	100
EBS	85.71	68.49	100	100	0	100	454.2	87.17
PayZippy	57.14	100	96	0	0	0	253.14	48.58
PayU	57.14	100	66	20	0	50	293.14	45.9
DirectPay	57.14	72.6	70	20	0	0	219.74	42.17

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Table-10. Membership Values. **Legend-7:** EMI-Equated Monthly Instalment.

Web service Components				Heuristics				
Web service	Credit card	Debit Card	Net Banking	Cash Cards	Mobile Payment	Multi Bank EMI	Total	%
Ccavenue	0.83	1	0.6336	0.33	0.16	0.125	3.0786	100
EBS	0.711393	0.68	0.66	0.33	0	0.5	2.881393	87.17
PayZippy	0.474262	1	0.6336	0	0	0	2.107862	48.58
PayU	0.474262	1	0.4356	0.066	0	0.25	2.225862	45.9
DirectPay	0.474262	0.72	0.462	0.066	0	0	1.722262	42.17

In the membership value Table, the weights are given to the attributes according to the priority with

Web service

respect to the application through which web service components has got its significant values.

Table-11. Class Identification with the help of Membership values. **Legend-8:** EMI-Equated Monthly Instalment

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Components				Heuristics					
Web service	Credit card	Debit Card	Net banking	Cash cards	MP	Multi bank EMI	Total	%	Class
Ccavenue	83	100	63.36	33	16	12.5	307.86	100	Excellent
EBS	62.0121278	59.2756	57.5322	28.7661	0	43.585	251.171	81.58	Excellent
PayZippy	23.039648	48.58	30.780288	0	0	0	102.3999	33.25	Satisfactory
PayU	21.7686258	45.9	19.99404	3.0294	0	11.475	102.1671	33.18	Satisfactory
DirectPay	19.9996285	30.3624	19.48254	2.78322	0	0	72.62779	23.58	Satisfactory

The membership value percentage is multiplied with entire row in the Table and corresponding Table-11 is obtained. Class Identification is done with the help of membership values.

In Figure-2, CCAVENUE and EBS web service components are precisely dominant than other components which is available in blue and red colours respectively and shows their high grand total with percentage.

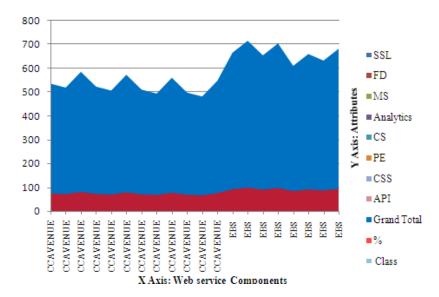


Figure-2. Web service components Vs attributes of priority based distributed measure (Table-4).

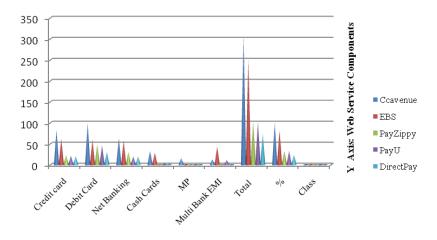
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In Figure-3, CCAVENUE and EBS web service components are predominant than other components

which is available in blue and red colours respectively.



X-Axis: Attributes

Figure-3. Attributes Vs Web service components.

Theil indexing

Theil indexing is applied to verify the purity level of the attributes. High purity attributes should always play a role to provide an accurate answer. Low priority attributes are not taken into account and the same is discarded. In this web service component six attributes for the payment options are considered because of their high

purity levels. For Table-12, the formula is depicted as follows:

$$T = 1/n \sum y_i / \ln(y_i / y) y,$$

where y_i is the value of the attribute and y is the mean of the attribute values.

Table-12. Theil Indexing. **Legend-9.** MB EMI-Multi Bank Equated Monthly Instalment

Web service components			Heuristics				
WS	Credit card	Debit Card	Net Banking	Cash Cards	MP	МВ ЕМІ	Class
CCA	0.47106113	0.14208453	0.128593916	1.529102448	8.047189562	-0.24033731	1.141085
EBS	0.21878587	-0.1964989	0.181641242	1.529102448	0	2.999491784	0.623332
PZ	-0.1785148	0.14208453	0.128593916	0	0	0	-0.29859
PayU	-0.1785148	0.14208453	-0.200490838	-0.364778641	0	0.509535634	-0.29926
DP	-0.1785148	-0.1603346	-0.164524566	-0.364778641	0	0	-0.36182
	0.15430248	0.06942002	0.073813669	2.328647615	8.047189562	3.268690107	0.804754
	0.0308605	0.013884	0.014762734	0.465729523	1.609437912	0.653738021	0.160951

RESULTS AND DISCUSSIONS

Table-3 consists of web services like CCAvenue and EBS with its required attributes. Finding class is the chief requirement for any type of training Table. Hence attributes in Table-4 are considered according to the priority of the application and the values are measured in terms with percentiles. The classes are identified according to the above said. Classes are fixed according to the threshold and are named as Excellent, Good, Fair and satisfactory if it lies in the range 90-100, 81-89, 71-80 and

below 70 respectively. PRISM methodology is applied to the training set in Table-5. Since the attribute SSL has got two varieties of bits like 128 and 256 bits. 256 bit has got a high probabilistic value and hence it is taken as a rule. That's why reduced data set is obtained. Fuzzy classification is applied for the Tables 6, 7 and 8 namely payment option, payment feature and payment price with different intricacies attributes for the methodologies and calculations. In Tables 9, 10 and 11 - Distributed Measures, Membership Values and class Identification

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with the help of Membership values Tables are attained by the way of priority based attributes classes using a unique and inevitable membership values. For gauging the purification of attributes that is all taken to measure different heuristics for the payment gateway web services and are measured via Theil Indexing. Here the values are in the positive side which proves that the heuristics that was taken in this paper is the appropriate one. By the end of this analysis it is all found that software component web services like CCAvenue and EBS has got a high reliability. The reliability is measured through the unique mapping between two methodologies such as Prism and Fuzzy classification.

7. OBSERVATION AND TECHNICAL IDEOLOGY OF THIS PAPER

For measuring web services, Heuristics plays a fundamental role and processing the instance available under the attributes will provide certain classes like Excellent, Good, Fair, Satisfactory and Poor. If some other heuristics is considered rather some intricate heuristics under the same segment that also provides the same result to the extent. In this paper two different types of heuristics are considered and two different methodologies like Crisp and Fuzzy applied that bestowed the same type of results after establishing a unique mapping between the two.

8. CONCLUSIONS

In our model we considered two different types of heuristics for the same components. One set of heuristics are measured via Crisp method - 'Prism' and another with Soft computing method - 'Fuzzy'. Fuzzy is applied to the more complex attributes of the first set of metrics. After gauging the components of web service using the methodologies and with a unique mapping, we observed that the web service component having reliability comes in the category of Excellent. In the first set of heuristics 8 metrics are taken for measurement and for the second set more intricate rather more complex and elaborate 32 metrics are considered for our empirical studies. T-test is applied to measure the mean difference between the set of attributes in two sets. The result shows the meagre difference and too it is acceptable. Through this we come to one real conclusion that formal attributes and a more unclear attributes provides alike results for web service components.

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