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BAHÇEŞEHİR ÜNİVERSİTESİ

INSTITUTE OF SCIENCE

COMPUTER ENGINEERING

HUMAN RESOURCE PERFORMANCE CLUSTERING BY USING SELF REGULATING CLUSTERING METHOD

Master Thesis

OSMAN KAYA

SUPERVISOR

ASSOC. PROF. DR. ADEM KARAHOCA

İSTANBUL 2008

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Name of the thesis: Human Resource Performance Clustering by Using Self Regulating Clustering Method

Name/Last Name of the Student: Osman KAYA

Date of Thesis Defense: 05.09.2008

The thesis has been approved by the Institute of Science.

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I certify that this thesis meets all the requirements as a thesis for the degree of Master of Science.

Assoc. Prof. Dr. Adem KARAHOCA

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This is to certify that we have read this thesis and that we find it fully adequate in scope, quality and content, as a thesis for the degree of Master of Science.

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ACKNOWLEDGMENTS

This thesis is dedicated to **my parents** for their patience and understanding during my master's study and the writing of this thesis.

I would like to express my gratitude to **Assoc. Prof. Dr. Adem Karahoca** for his great contribution to my career by admitting me as a research assistant and then make me do many researches on various topics and make me feel that I can accomplish everything if I really want and work patiently.

I would like to thank CSE faculty and research assistants for making my two years at Bahçeşehir University a great experience.

Finally, I would like to thank all my friends for their motivation.

ABSTRACT

HUMAN RESOURCE PERFORMANCE CLUSTERING BY USING SELF REGULATING CLUSTERING METHOD

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Supervisor: Assoc. Prof. Dr. Adem Karahoca

August, 2008, 41 pages

In organizational performance evaluation, performance of each staff plays a key role for organization. Although, the whole is greater than the sum of its parts, outstanding personnel performances determine the performance of the whole organization. At this point, an understanding and awareness of individual differences in performance stands as a critical point in making decisions related to promotion, wage determination, fringe benefit allotment and etc. since, those decisions are directly related to personnel motivation, retention and further organizational performance. Data mining and clustering methods can be used in personnel performance evaluation. After gathering personnel performance data from human resource department, the need to take some specific results about performance measurement and evaluation may be addressed by clustering methods. By clustering, a distinction between personnel by grouping them by their performance grades both assists attaining a bird's eye view of the general performance of the organization and each staff's contribution level to the organizational performance. For evaluating cluster numbers using x-mean algorithm, the algorithm finds optimum cluster number for cluster distribution. Hence, our problem of an optimum clustering schema for personnel performance data may be addressed. These results show the usefulness of an innovative technique when applied to research so far conducted through traditional methodologies, and brings to the surface questions about the universal applicability of the widely accepted relationship between superior HRM and superior business performance.

Keywords: Human resource management, online self regulating clustering algorithm, data mining, c-mean-online clustering, x-mean algorithm, performance evaluation, organizational performance.

ÖZET

İNSAN KAYNAKLARI PERFORMANSI KÜMELEMEDE KENDİLİĞİNDEN

DÜZENLENEN KÜMELEME YÖNTEMİNİN KULLANILMASI

Kaya, Osman

Yüksek Lisans, Bilgisayar Mühendisliği Bölümü

Tez Yöneticisi: Doç. Dr. Adem Karahoca

Temmuz, 2008, 41 sayfa

Organizasyonel performans ölçümünde, her bir çalışanın performansı anahtar rol oynamaktadır. Bütün, parçaların toplamından büyük olsa da, öne çıkan çalışanların performansı tüm organizasyonun performansını belirlemektedir. Bu noktada, çalışanlar arası performansların farklılıklarının anlaşılması ve fark edilmesi, terfi, ücret ve yan haklar gibi konularda alınacak kararlarda hayati önem taşımaktadır, çünkü alınan kararlar, çalışanların motivasyonu ve organizasyonda tutulabilmesi daha yüksek organizasyonel performans için doğrudan nedensellik ilişkisi taşımaktadır. Bu noktada, veri madenciliği ve kümelendirme yöntemlerinden yardım alınabilmektedir. İnsan kaynakları biriminden çalışan performans puanları elde edildikten sonra, verilerden belirli sonuçlara ulaşılabilecek yorumlar elde edebilmek için kümelendirme yöntemleri kullanılabilir. Kümelendirme sayesinde, çalışanların performans puanlarına göre farklı kümelerde incelenmesi, hem organizasyonun genel performansına kuş bakışı bir bakış açısından bakılmasına, hem de her bir çalışanın organizasyona bireysel katkısının anlaşılmasına yardımcı olacaktır. X-mean algoritmasından yararlanarak en uygun küme adedi hesaplanabilir. Böylece, amacımız olan çalışanların performans verilerinin en uygun biçimde kümelere göre ayırt edilmesi gerçekleştirilebilir. Sonuçlar, geleneksel yöntemlere göre daha ileri, yararlı ve yenilikçi sonuçlara ulaştırmakta ve genel Kabul gören, daha iyi insan kaynakları yönetimi ve iş performansı ilişkisini açıklayabilmektedir.

Anahtar Kelimeler: İnsan kaynakları yönetimi, çevrimiçi kendiliğinden düzenlenen kümeleme algoritması, kümeleme algoritması, veri madenciliği, c-mean çevrimiçi kümeleme, x-mean algoritması, performans ölçümü, organizasyonel performans.

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LIST OF ABBREVIATIONS

Fully self organizing simplified adaptive resonance theory	:	FOSART
Fuzzy adaptive resonance theory	:	fuzzy ART
Fuzzy learning vector quantization	:	FLVQ
Growing neural gas	:	GNG
Human resource management	:	HRM
Magnetic resonance image	:	MRI
One prototype take one cluster	:	OPTOC
Radial basis function networks	:	RBFN
Self organizing map	:	SOM
Self regulating clustering algorithm	:	SRCA
Self-splitting competitive learning	:	SSCL
Validity guided (re)clustering	:	VGC

LIST OF FORMULAS

1. INTRODUCTION

Human Resources effectiveness is a critical issue. Human Resources procedures require a strong emphasis for improving decisions about human capital. Human capital determines how far a business may improve and reach its targets. Thus, in order to understand the dynamics of motivation of the personnel and have a clear perception of the improvement of the personnel performance, the performance data shall be analyzed utilizing the most appropriate statistical techniques to yield the desired practical information (Berman, West, Wang 1999).

This study presents a self-regulating clustering algorithm (SRCA) for identifying a suitable cluster configuration without a priori knowledge of the given data set. A novel idea for cluster boundary estimation has been proposed to effectively group data points into compact hyper-elliptic-shaped boundaries. In the boundary estimation, two important vectors, a virtual cluster spread and a regulating vector, have been designed to regulate the boundaries of clusters to enclose suitable data points in suitable clusters. With the integration of growing and merging mechanisms, the proposed SRCA was able to reveal a compact cluster configuration which is close (or equal) to the actual one of the given data set (if it exists). Computer simulations on synthetic data sets as well as benchmark examples have been used to validate the effectiveness of the SRCA (Wang 2007).

Clustering analysis is regarded as the process of separating a set of data into several subgroups on the basis of their similarity (Jain and Dubes 1988). In the past decades, clustering techniques have been recognized as an effective tool to extract essential knowledge from large volumes of data to solve problems from different scientific domains as well as commercial sectors (Baraldi and Blonda 1999). Despite these successful applications, there stil remain some important questions to be answered. One of these questions is how to determine a cluster number with suitable cluster prototypes to properly represent the data. To solve such a problem, a great amount of research effort has been directed to equipping clustering algorithms with systematic frameworks to automatically reveal the cluster configuration of data sets (Chinrungrueng and Sequin 1995).

In order to figure out the numbers of clusters of the data, we implemented x-means algorithm (Pelleg and Moore 2000).

1.1. PROBLEM DEFINITION

This study aims to explore the following research questions;

1. Which organizational departments contribute most to the differentiation between superior and lower performing organizations?
2. How departments' contribution to the organizational performance might be measured and differentiated.
3. Do superior-performer organizations form a specific pattern that distinguishes them from lower performer?
4. How personnel contribution to the organizational performance might be measured and how a better comparison might be attained among personnel performance?

The objective of cluster analysis is the classification of objects according to similarities among them, and organizing of data into groups. Clustering techniques are among the unsupervised methods, they do not use prior class identifiers. The main potential of clustering is to detect the underlying structure in data, not only for classification and pattern recognition, but for model reduction and optimization. Different classifications can be related to the algorithmic approach of the clustering techniques. Partitioning, hierarchical, graph-theoretic methods and methods based on objective function can be distinguished.

This working is aid taking some decisions for Human Resource department.

2. LITERATURE SURVEY AND BACKGROUND

At the past, many scientists made researches on the topic of human resources performance evaluation and classification through clustering. List of literature is listed below as follows:

2.1. Data Mining to Improve Personnel Selection and Enhance Human Capital

(Chien and Chen 2008) developed a data mining framework based on decision tree and association rules in order to generate useful rules for personnel selection and retention. The study focuses on quality of human capital at high-tech companies. The main problems that high-tech companies are listed as high turnover rates and difficulties in recruiting right talents, who are the most suitable to company's own organizational structure. Also, the mined results of the study is assessed to help improving human resource management activities including job redesign, job rotation, mentoring, and career path development. It is assessed that with an effective personnel selection process, organizations can find the suitable talents at the first time to improve retention rate and generate better performance.

The developed data mining framework to extract rules from the relationships between personnel profile data and their work behaviors, and developed strategies with domain experts in the case company and most of the suggestions are implemented. The study used applicant's demographical data and work experience to predict their work performance and retention. It is also stated that further data may be used such as address, the rank or scores in school and number of owned licenses and uncover buried relationships, and some other turnover reasons other than considered in the study may be subject of further study.

In the study, decision tree is used for data mining, since, it is easier to perceive and offers acceptable level of accuracy. The empirical study revealed practical viability of this approach for extracting rules for human resource management in the semiconductor industry. Also, it is stressed that this methodology can be applied to other occupations like operators and management level occupations, and to other industries to find matched talents to enhance human capital, and a screening mechanism working on an information system that processes large volumes of personnel data may be used for reducing recruiter's visible and invisible costs.

2.2. Human Resource Management And Performance Measurement By Neural Network Analysis

(Stavrou, Charalambous, and Spiliotis 2007) utilizes an innovative research methodology known as Kohonen's Self-Organizing Maps to explore the connection between human resource management as a source of competitive advantage and perceived organizational performance in the European Union private and public sectors. Results of the study revealed the usefulness of an innovative technique when applied to research so far conducted through conventional methodologies, and caused questions to arise about the universal applicability of the widely accepted relationship between better human resource management and better business performance.

2.3. The Impact of Human Resource Management on Organizational Performance

(Becker and Gerhart 1996) emphasizes the importance of human resource management in its influence on organizational performance. The paper addresses the link between human resource management and organizational performance in unique view of angle and provides suggestions regarding a better perception about the issue.

2.4. Attracting and Retaining Talent

(Holland, Sheehan, and Cieri 2007) approaches to the skilled labor attraction, recruitment, and retention issue from a competitive advantage point of view. The paper examined responses from 1372 Australian human resources professionals who participated in an online survey of a national human resource professional association and results are interpreted with respect to human resource efforts to attract, develop, and retain talent.

The paper concludes that in critical human resource development areas, associated with retention such as training, job design, skill development, careers management and team building, results indicate a lower level of resource allocation, and hence, lack of resource allocation suggests weaknesses for Australian companies in competition for attracting, recruiting, and retaining skilled worker.

3. MATERIAL AND METHOD

3.1. About Data Set

In this study, the data set utilized is gathered from a special firm's employees' yearly performance scores data covering a period of two years.

Table 3.1: Description of dataset columns

Data Field	Description
Personnel Id	Unique personnel number using for identification
Department Id	Indicate personnel department
Performance Grade	For each performance criteria managers give their employees a performance grade
Weight	Each criteria have specific weight
Description	Description for performance criteria
Year	All employee performance evaluation least once in one year.
Line Type	Performance criteria have two type, capability and target.

Data fields for 1100 employees include the department in which the employee works, the scores for succeeding two years, and the base value for scoring scale. Those employees who resigned or recruited during the time period which data covers are excluded.

There are capability and performance target items for every personnel in the system. Namely, every organizational role has its own capability and performance based targets weighted at varying magnitudes, such as, executive officer, manager, supervisor, associate, internal auditor, marketing personnel, accounting personnel and teller. Below, capability and performance target items for three organizational roles, namely, manager, internal auditor and teller are listed along with performance evaluation scale.

Table 3.2: Performance target items for managers

Retail fund lending
Retail fund lending commissions collection
Gathering retail customers' deposit
Number of given charge credit cards

Number of new internet banking customers
Number of given debit cards
Branch income
Total of new credit limits
Total amount of banking services income
POS turnover
Success orientation
Analytical thinking
Cooperation
Personal communication and persuasion capabilities
Customer oriented marketing
General communication and information sharing
Stress resistance
Total amount of foreign trade transactions commissions collection
Total amount of foreign trade transactions volume
Corporate fund lending commissions collection
Total volume of corporate deposit accounts
Total volume of corporate saving accounts
Total volume of corporate loans
Total amount of letter of guarantee commissions collection
Total volume of letter of guarantees
Net profit/loss

The performance agreement between the Senior Manager and the General Manager must set out expectations and the means by which performance against these expectations will be assessed. A new performance agreement should not be entered into until the previous year's performance review has been completed. The expectations in the performance agreement should be consistent with the General Manager's duties and functions as identified in the Standard Contract (see attached). The performance agreement should be realistic and achievable and the Council should provide adequate resources to enable the General Manager to perform his/her duties and functions in Table 3.2

A fundamental component of any performance agreement is the ability to measure performance at both the organisational and individual level. This will require both quantitative and qualitative measures.

Table 3.3: Performance target items for internal auditors

Managing expenditures in line with the budget
Attending at least three professional training programs within the accounting year
Completing branch and department audits as planned
Conducting customer and risk oriented research and development activities, reporting the results
Educating the branch and department personnel concerning corporate policy and procedures
Observing corporate compliance with Risk Management Decree
Observing corporate compliance with related codes and regulations
Sharing professional judgment regarding ongoing operations' acceptable risk levels
Developing brand new audit techniques
Reporting high risk areas and suggesting solutions
Supporting practical and theoretical professional training of new personnel
Good personal relations with colleagues. Completing tasks and duties adequately. Attending to corporate social activities
Communicating and information sharing with other departments on risk and audit related issues
Developing solutions for problems confronted during audits
Completing projects submitted by the manager and succeeding at written examinations
Analytical thinking
Customer orientation

Success orientation
Communication and information sharing
Planning and organization

The internal audit function is established to provide independent, objective assurance and consulting services designed to add value and improve the organization's operations. It helps the organization accomplish its objectives by bringing a systematic, disciplined approach to evaluate and improve the effectiveness of risk management, control, and governance processes. In Table 3.3 list internal auditor evaluation performance criteria.

Table 3.4: Performance target items for tellers

Attaining average transaction time lower than 105% of corporation's average transaction time.
Classifying recurring transactions (cash withdrawal, cash machine daily control, etc.)
Classifying and monitoring outgoing cash transaction to other banks
Receiving less than 4 yearly customer complaints while at most 2 of them are action requiring complaints
Success orientation
Adaption to change
Cooperative working
Communication and information sharing
Customer orientation
Stress resistance
Persuasive influence

Table 3.4 displays performance target items for teller prepares by human resource department for evaluating teller performance and improvement.

Table 3.5: Performance evaluation scale

Performance	Grade	Evaluation
Higher than 110%	5	High Performance above responsibilities
Between 101% and 109%	4	Performance above responsibilities
Between 86% and 100%	3	Fully met responsibilities
Between 75% and 85%	2	Performance below responsibilities
Lower than 74%	1	Unsuccessful

As a result of this process, those listed criteria are evaluated by managers for every individual personnel and a grade between 1 to 5 is attached to the personnel. However, while some managers expect the personnel to accomplish 3 to 4 targets, some others may expect 20 to 30 to be accomplished. In this case, the number of target items gains relative importance as well as the grade attached.

There is also the issue of department IDs. That is for demonstrating that if two separate departments that had the same grade as at the example above in fact had different grades. This is intented for benchmarking.

Our intent is to match all personnel performance data for specific results. Such as, benchmarking is annual performance data for two different departments. In this study we use only performance grade, line count and department information.

Those fields below listed are used for this study: Personnel Id: for user identification; Department Id: for benchmarking; Grade: Performance grade for all criteria; Also in calculate line, count for each personnel grade. However, all personnel information are retained on HR information system, so if we can evaluate different scenarios, we can demonstrate personnel performance and;

i. Age
ii. Gender
iii. Marital status
iv. Degree
v. School/school tier
vi. Major
vii. Work experience

3.2. Clustering Model

At the past, many scientists made researches on the topic of classification through clustering. List of literature is listed below as follows:

3.2.1. Fuzzy Clustering Algorithms for Pattern Recognition

(Baraldi and Blonda 1999) proposed equivalence between the concepts of fuzzy clustering and soft competitive learning in clustering algorithms on the basis of the existing literature. Moreover, a set of functional attributes is selected for use as dictionary entries in the comparison of clustering algorithms. Five clustering algorithms taken from literature are reviewed, assessed and compared on the basis of the selected properties of interest. These clustering models are, (1) self-organizing map (SOM); (2) fuzzy learning vector quantization (FLVQ); (3) fuzzy adaptive resonance theory (fuzzy ART); (4) growing neural gas (GNG); (5) fully self organizing simplified adaptive resonance theory (FOSART). Although our theoretical comparison is fairly simple, it yields observations that may appear paradoxical. First, only FLVQ, fuzzy ART, and FOSART exploit concepts derived from fuzzy set theory. Second, only SOM, FLVQ, GNG, and FOSART employ soft competitive learning mechanisms, which are affected by asymptotic misbehaviours in the case of FLVQ, i.e., only SOM, GNG, and FOSART are considered effective fuzzy clustering algorithms.

3.2.2. Validity Guided (Re)Clustering with Applications to Image Segmentation

(Bensaid, Hall, Bezdek, Clarke, Silbiger, Arrington, Murtagh, 1996) stresses that the goal when clustering algorithms are applied to image segmentation, the goal is a adequate classification. However, clustering algorithms do not directly optimize classification duality. As a result, they are susceptible to two problems: 1) the criterion they optimize may not be a good estimator of true classification quality. And 2) they often admit many solutions. The paper introduces an algorithm that uses cluster validity to mitigate problems 1 and 2. The validity-guided (re)clustering (VGC) algorithm uses cluster-validity information to guide a fuzzy (re)clustering process toward better solutions. It starts with a partition generated by a soft or fuzzy clustering algorithm. Then it iteratively alters the partition by applying (novel) split-and-merge operations to the clusters. Partition modifications that result in improved partition validity are retained. VGC is tested on both synthetic and real-world data. For magnetic resonance image (MRI) segmentation, evaluations by radiologists show that VGC outperforms the (unsupervised) fuzzy c-means algorithm, and VGC's performance approaches that of the (supervised) k-nearest-neighbours algorithm.

3.2.3. Optimal Adaptive K-Means Algorithm with Dynamic Adjustment of Learning Rate

(Chinrungrueng and Sequin 1995) states that adaptive k-means clustering algorithms have been used in several artificial neural network architectures, such as radial basis function Networks or feature-map classifiers, for a competitive partitioning of the input domain. The paper presents an enhancement of the traditional k-means algorithm. It approximates an optimal clustering solution with an efficient adaptive learning rate, which renders it usable even in situations where the statistics of the problem task varies slowly with time. This modification is based on the optimality criterion fort he k-means partition stating that: all the regions in an optimal k-means partition have the same variations if the number of regions in the partition is large and the underlying distribution for generating input patterns is smooth. The goal of equalizing these variations is introduced in the competitive function that assigns each new pattern vector to the appropriate region. To evaluate the optimal k-means algorithm, the authors first compare it to other k-means variants on several simple tutorial examples, then the authors evaluate it on a practical application: vector quantization of image data.

3.2.4. Self-Splitting Competitive Learning Through a New Online Clustering Paradigm

(Zhang and Liu 2002) states that clustering in the neural-network literature is generally based on the competitive learning paradigm. The paper addresses two major issues associated with conventional competitive learning, namely, sensitivity to initialization and difficulty in determining the number of prototypes. In general, selecting the appropriate number of prototypes is a difficult task, as we do not usually know the number of clusters in the input data a priori. It is therefore desirable to develop an algorithm that has no dependency on the initial prototype locations and is able to adaptively generate prototypes to fit the input data patterns. Authors present a new, more powerful competitive learning algorithm, self-splitting competitive learning (SSCL), which is able to find the natural number of clusters based on the one-prototype-take-one-cluster (OPTOC) paradigm and a self-splitting validity measure. It starts with a single prototype randomly initialized in the feature space and splits adaptively during the learning process until all clusters are found; each cluster is associated with a prototype at its center. Authors have conducted extensive experiments to demonstrate the effectiveness of the SSCL algorithm. The results show that SSCL has the desired ability for a variety of applications, including unsupervised classification, curve detection, and image segmentation.

3.2.5. Dynamic Cluster Generation for a Fuzzy Classifier with Ellipsoidal Regions

(Abe 1998) discusses a fuzzy classifier with ellipsodial regions that dynamically generate clusters. First, fort he data belonging to a class is defined a fuzzy rule with an ellipsodial region. Namely, using the training data for each class, the center and the covariance matrix of the ellipsodial region fort he class is calculated. Then the fuzzy rules are tuned, i.e., the slopes of the membership functions, successively until there is no improvement in the recognition rate of the training data. Then if the number of the data belonging to a class that are misclassified into another class exceeds a prescribed number, a new cluster to which those data belong and the associated fuzzy rule is defined. Then the newly defined fuzzy rules in the similar way as stated above are tuned, fixing the already obtained fuzzy rules. Generation of clusters and tuning of the newly generated fuzzy rules are iterated until the number of the data belonging to a class that are misclassified into another class does not exceed the prescribed number. The method is evaluated using thyroid data, Japanese Hiragana data of vehicle licence plates, and blood cell data. By dynamic cluster generation, the generalization ability of the classifier is improved and the recognition rate of the fuzzy classifier fort he test data is the best among the neural network classifiers and other fuzzy classifiers if there are no discrete input variables.

3.2.6. Efficient Function Approximation Using an Online Regulating Clustering Algorithm

(Wang and Wang 2004) presents online self-regulating clustering algorithm (SRCA) to construct parsimonious radial basis function networks (RBFN) for function approximation applications. Growing, merging and splitting mechanisms with online operation capability are integrated into the proposed SRCA. These mechanisms enable the SRCA to identify a suitable cluster configuration without a priori knowledge regarding the approximation problems. Also, a novel idea for cluster boundary estimation has been proposed to maintain the resulting clusters with compact hyper elliptic shaped boundaries. Computer simulations reveal that RBFN constructed by the SRCA can approximate functions with a high accuracy and fast learning convergence. Benchmark examples and comparisons with some existing approaches have been conducted to validate the effectiveness and feasibility of the SRCA for function approximation problems.

3.3. ONLINE SELF REGULATING SYSTEM

3.3.1. Finding Cluster Numbers

In order to figure out cluster numbers, x-means algorithm is implemented. X-means algorithm is implemented to figure out the optimum number of clusters that fits best to the data. Other clustering algorithm takes cluster number and distributes items for this number. In this situation don't know optimum cluster number, so we must use a algorithm for calculate optimum cluster number. X-mean is an ideal algorithm for this situation.

3.3.2 Online Self Regulating Cluster Analysis Design

For online clustering algorithms, growing mechanisms are frequently used to dynamically adapt new data for the identification of cluster configuration (Wang 2007), (Abe 1998). In the design of growing mechanisms, the range of cluster boundaries plays a decisive role in the clustering outcome. However, this parameter is difficult, if not impossible, for users to acquire in advance. An aligned clustering algorithm that uses a pre-specified constant to define the variance of initial clusters and then grows clusters for new data that are not covered by the existing clusters (Juang and Lin 1998). If the pre-specified variance of clusters is small, the number of clusters will be large in the final clustering result. Contrarily, all the data will be covered by one cluster if the variance is too big. That is, the outcome of this clustering algorithm is fully governed by this constant. A satisfactory result may require some trial-and-error effort or prior knowledge of the data distribution. Unlike using a constant for cluster initialization, the authors in (Zhang and Liu 2002) constructed a dynamic neighborhood for a randomly assigned cluster prototype and gradually reduced its size to zero to guarantee the convergence of the prototype. This idea was named a one-prototype-take-one-cluster. In their algorithm, the number of clusters grows by the evaluation of a split validity criterion that is satisfied when the distance between the prototype (a) Cluster boundary estimation using rectangles to enclose elliptical clusters. (b) The moving trajectories of the regulating vectors and the variation of cluster variances and the centroid of the cluster is less than a predefined threshold. The bigger the threshold is, the poorer the accuracy of the clustering. Some adjacent clusters merge into one cluster since there is no merging criterion.

From the above literature review, we conclude that a reliable clustering algorithm should be capable of 1) cooperatively integrating both growing and merging mechanisms into a systemic framework, 2) dynamically regulating the size as well as the number of clusters, and 3) effectively extracting the information of cluster distribution. These three main properties have directed our research effort to developing the proposed self-regulating clustering algorithm (SRCA). A novel idea has been formulated to dynamically regulate cluster boundaries with the integration of growing and merging mechanisms to systematically reveal the number as well as the prototypes of the clusters.

The proposed SRCA is a dynamic clustering algorithm that is capable of growing and merging clusters to reveal the natural or close to natural cluster configuration for a given data set. During the clustering process, data are queried randomly and passed to the algorithm. Two clusters are initialized in the initial cluster configuration with the following conditions: 1) the virtual-spread vectors of the two initial clusters are assigned as zero vectors; 2) the cluster centers are randomly chosen from the data set; and 3) the regulating vectors are randomly assigned far away from the centers. The clustering process of the SRCA proceeds with these two initial clusters to group each set of incoming data with either growing or merging mechanisms. The first step is to check if the incoming data $\boldsymbol{x}_n$ is located inside the existing clusters in both input and output spaces. Due the hyper-elliptic shape of the clusters, we can confirm whether the condition is satisfied by the following equations:

$$R_{i,n} = \left| r_{i,n} - m_{i,n} \right|, i = 1, \ldots, c. \qquad (1)$$

$$\Lambda_{i,n} = \frac{\left\| x_{1,n} - m_{i1,n} \right\|^2}{R_{i1,n}^2} + \frac{\left\| x_{2,n} - m_{i2,n} \right\|^2}{R_{i2,n}^2} + \ldots + \frac{\left\| x_{k,n} - m_{ik,n} \right\|^2}{R_{ik,n}^2}, \qquad (2)$$

where $\boldsymbol{m}_{i,n} = [m_{i1,n}, m_{i2,n}, \ldots, m_{ik,n},]^T$, $\boldsymbol{R}_{i,n} = [R_{i1,n}, R_{i2,n}, \ldots, R_{ik,n},]^T$, and the components of **R** denote the radiuses of the *i*th cluster boundary. Note that the values of $\Lambda_{i,n}$, $i = 1,\ldots, c$, are computed to determine the locations of the incoming data in both the input and output spaces. If the data is covered by the existing clusters, the values of $\Lambda_{i,n}$ in both the input and output spaces should be less than (or equal to) 1. We treat the incoming data as an internal point. Otherwise, we regard the incoming data as an external point of the existing clusters.

If the incoming data is an external point, before a new cluster is created, the data will be further examined by two additional criteria: 1) the constraint of input-output mapping consistency (MC), and 2) the limitation of cluster variances (CV) in the output space. These two criteria are proposed so as to prevent false determination caused by the immature coverage of clusters in the initial stage. The first criterion was adopted from our previous study and is based on a general assumption for data clustering: similar input patterns should map to similar output patterns. The input-output mapping relationship is defined as “consistent” if two clusters are reciprocally close in Euclidean distance to each other in both input space and output space. Then these two clusters can be considered to be from the same class and thus can be merged together. Otherwise, if two clusters are reciprocally close in the input space but are far away in the output space, then these two clusters can belong to different classes. Here, we treat the incoming data as the centroid of a candidate cluster and use the above concept to evaluate the mapping relationship between the existing clusters and the candidate cluster. In the initial clustering stage, the coverage of each cluster is gradually broadened to group similar data into the same cluster. If the creation of new clusters is solely based on whether the data is an external point of the existing clustering, then some redundant clusters can be generated due to the immature cluster coverage in the initial stage. Hence, we introduce the mapping consistency as an important criterion for the determination of the execution of the growing mechanism. In addition, if the incoming data satisfies the mapping consistency with a cluster, say the i^{th} cluster, but is not covered by all the existing clusters, we consider that the incoming data is a member of the i^{th} cluster. The limitation of CV in the output space is introduced as a sifting criterion if the following inequality is satisfied.

$$\delta_i = \sqrt{\sigma_{i,1}^2 + \sigma_{i,2}^2 + \ldots. + \sigma_{i,k}^2} < T, \tag{3}$$

where δ_i is the output variance of the i^{th} cluster containing the incoming data and T is a pre-specified constant. The reason why we only consider the output variance is that the output clusters are directly related to the performance of data classifications.

If the incoming data does not satisfy any one of the above two criteria, a new cluster will be created with the incoming data as its centroid. Otherwise, the existing cluster configuration will be updated with respect to the incoming data. On the other hand, if the incoming data is an internal point, the cluster boundary estimation approach will be employed to update the cluster parameters, such as the cluster centers, virtual-spread vector, and regulating vectors.

4. PROBLEM SOLUTION AND FINDINGS

4.1. Application of Performance Clustering By Using Self Regulating Clustering to the Human Resource Performance Data

In order to figure out how many clusters are present, first x-mean algorithms are calculated. The result of the x-mean algorithm yields the centroids. After this point every datum included to the data set is first determined in which cluster it will be included and then the regulator vector is updated. Finally, the ellipse is depicted on the regulator vector value.

In this study, our intent is to apply Self Regulating Clustering Method to evaluate HR performance by using cluster analysis.

In system identification, the purpose of clustering is to find relationships between independent system variables and future values of dependent variables. One should, however, realize that the relations revealed by clustering are just causal associations among the data vectors, and as such do not yet constitute a prediction model of the given system. To obtain such a model, additional steps are needed.

System Inputs;

Personnel Id: using for identification

Performance grade: takes from relevant manager

Lines of grade for each personnel: count of grade line

Table 4.1: Simple input data

Personnel Id	Grade	# of evaluation of criteria
194	4	28
196	2	22
197	3	17
199	2	22
215	3	34

Output:

Dependent on input values estimate cluster count and distribution.

System take 1100 personnel data and 17,000 capability or performance target row for relevant. First find cluster count using X-mean algorithm –find 4 cluster - , later find and show these data cluster distributions using self regulating method.

X-mean results

X-mean algorithm applies for finds optimum number of cluster count, average of distance for each cluster point and standard deviation for each cluster.

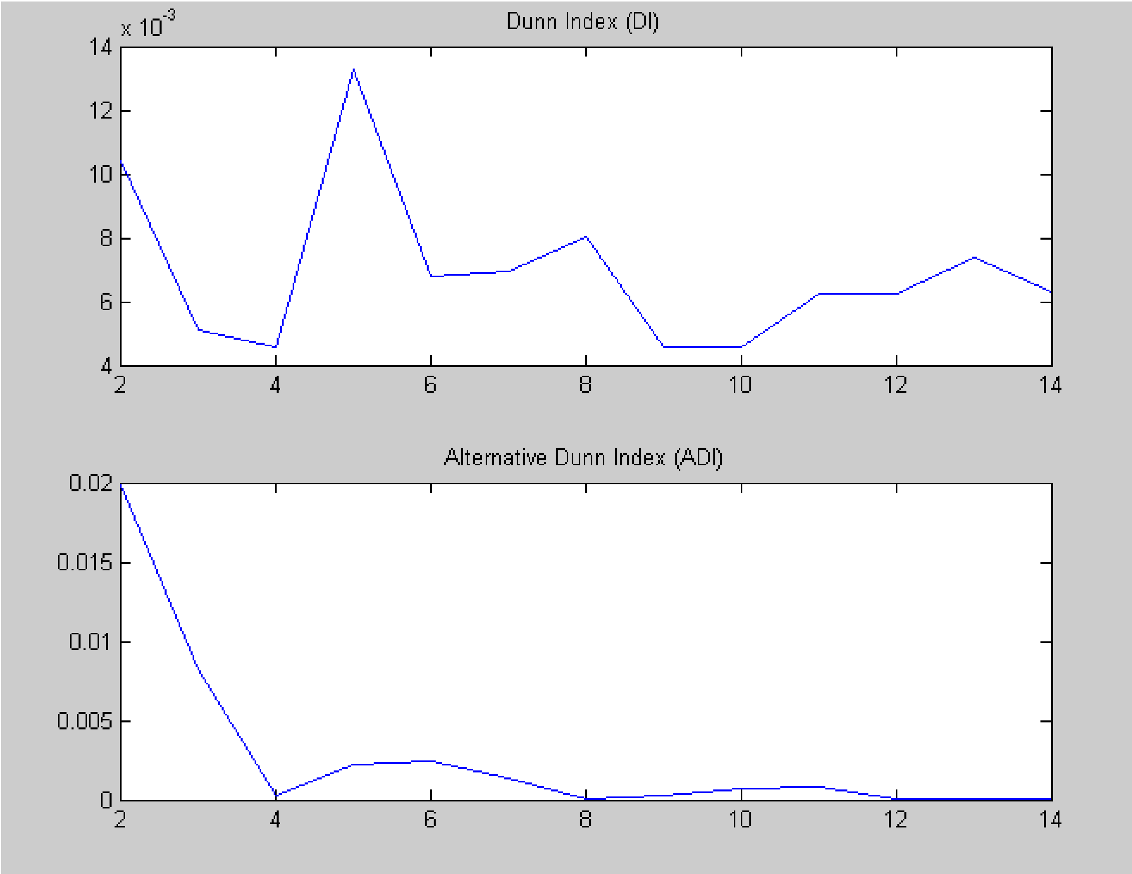


Figure 4.1: Result of finding optimum cluster number using X-mean algorithm.

Dunn's Index (DI): This index is originally proposed to use at the identification of "compact and well separated clusters". So the result of the clustering has to be recalculated as it was a hard partition algorithm.

Alternative Dunn Index (ADI): The aim of modifying the original Dunn's index was that the calculation becomes more simple, when the dissimilarity

In Figure 3.1 shows optimum number of cluster for x-mean algorithm. Dunn Index and Alternative Dunn Index shows ideal cluster number, our algorithm select minimum count for cluster number.

After finding this information about clusters, this data is passed on the c-means algorithm.

Table 4.2: X-mean algorithm configuration parameters

Parameter	Value
Requested iterations	1
Iterations performed	1
Splits prepared	2
Splits performed	2
Cutoff factor	0.5
Percentage of splits accepted by cutoff factor	0 %
Cutoff factor	0.5
Cluster centers	4 centers

X-Means is K-Means extended by an Improve-Structure part in this part of the algorithm the centers are attempted to be split in its region. The decision between the children of each center and itself is done comparing the BIC-values of the two structures.

X-mean calculates and performance parameter shows on Table 3.2. Parameter “cutoff factor” means takes the given percentage of the spitted centroids if none of the children win.

Mean and standard deviation values for all clusters are as summarized below:

Table 4.3: Clusters

Cluster	Mean	Standard Deviation
0	0.6005	0.3861
1	0.3907	0.1843
2	1.0	-0.8443
3	0.7994	0.6080

Table 4.3 displays findings for cluster number, means and standard deviation for each cluster. This information is using by c-mean algorithm.

Table 4.4: Clustered Instances

Cluster	Number of row	Percent of Row
0	633	57%
1	140	13%
2	30	3%
3	311	28%

Table 3.4 displays number of data for each cluster and percent. We can see distribution of data on charts.

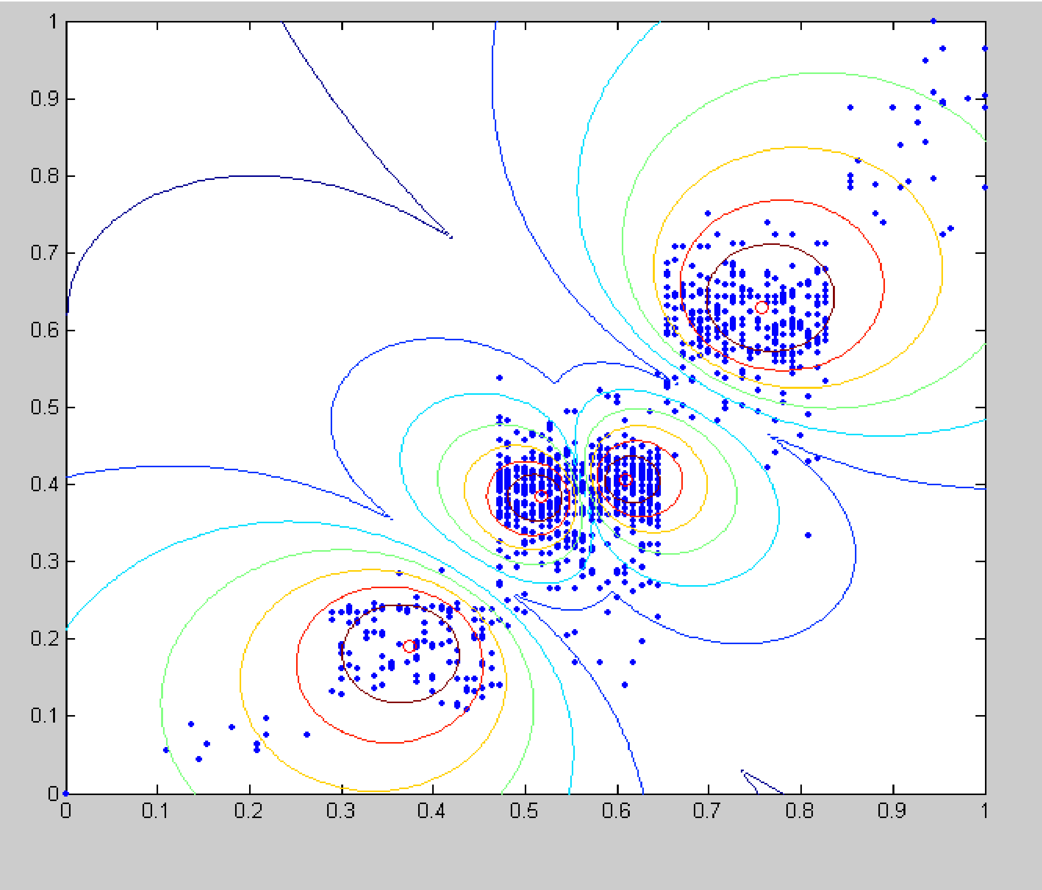


Figure 4.2: Result of Fuzzy C-means algorithm by the synthetic overlapping performance data with normalization.

The Fuzzy C-means clustering algorithm uses the minimization of the fuzzy C-means functional. There are three input parameter needed to run this function: as the number of clusters or initializing partition matrix. The one latter parameter has their default value 5, if they are not given by X-mean algorithm. The function calculates with the standard Euclidean distance norm, the norm inducing matrix is an NXN identity matrix. The result of the partition is collected in structure arrays. One can get the partition matrix cluster centers, the square distances, the number of iteration and the values of the C-means functional at each iteration step.

In Fig. 4.2 the '.' remark the data points, the 'o' the cluster centers, which are the weighted mean of the data. The algorithm can only detect clusters with circle shape, that is why it cannot really discover the orientation and shape of the cluster "right below" in Fig. 4.2 the circles in the contour-map are a little elongated, since the clusters have correct on each other. However the Fuzzy C-means algorithm is a very good initialization tool for more sensitive methods

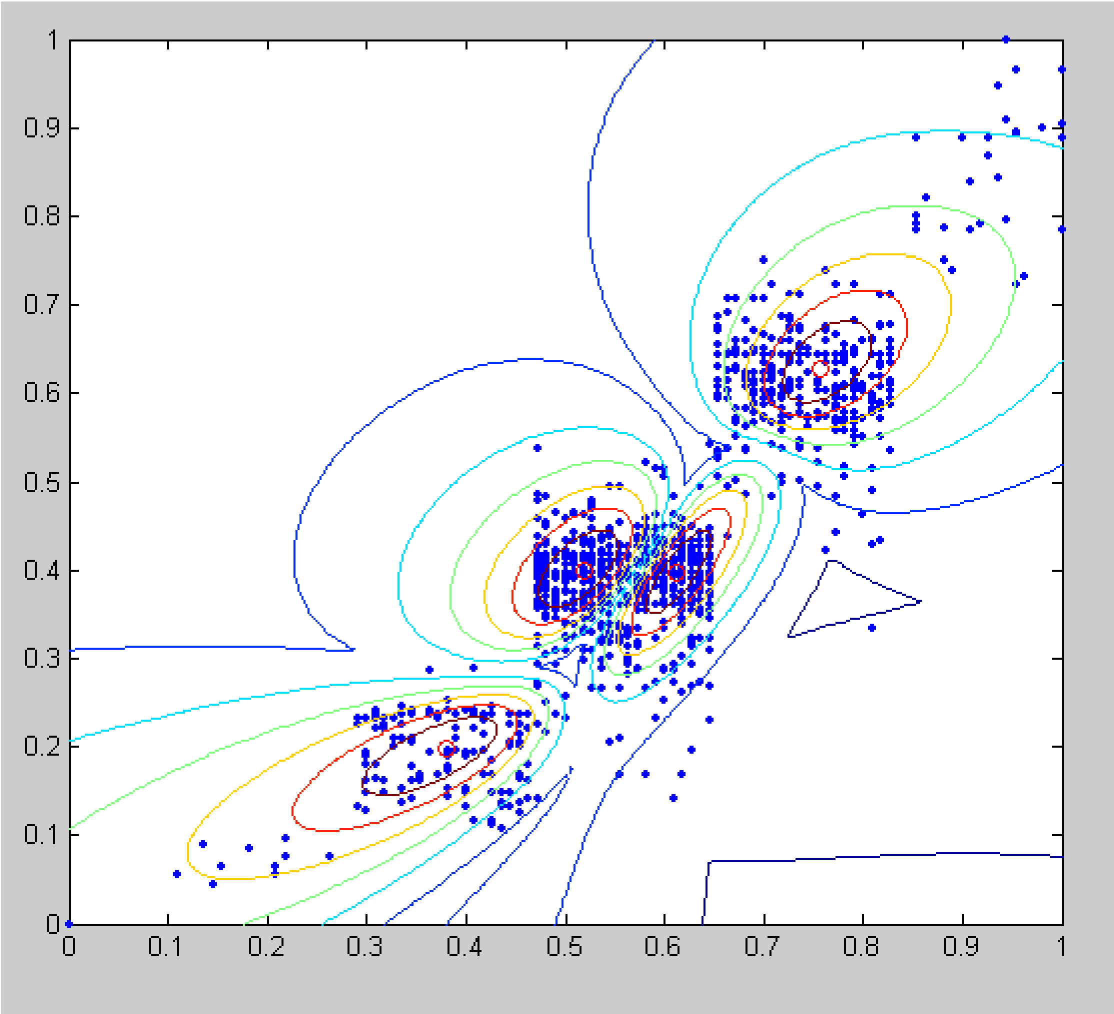


Figure 4.3: Result of Gustafson-Kessel algorithm by the synthetic overlap-ping performance data with normalization.

The clustering algorithm forces, that each cluster has its own norm inducing matrix Ai, so they are allowed to adapt the distance norm to the local topological structure of the data points. The algorithm uses the Mahalanobis distance norm.

There are two numerical problems with Gustafson-Kessel algorithm.

1. If there is no prior knowledge, the prior probability for each cluster. is 1 for each cluster, so the GK algorithm can 2^{nd} only clusters with approximately equal volumes.

2. A numerical drawback of Gustafson-Kessel algorithm is: When an Eigenvalue is zero or when the ratio between the maximal and the minimal Eigenvalue, i.e. the condition number of the covariance matrix is very large, the matrix is nearly singular.

Also the normalization to a fixed volume fails, as the determinant becomes zero. In this case it is useful to constrain the ratio between the maximal and minimal eigenvalue, this ratio should be smaller than some predefined threshold.

In Fig. 4.3 the '.' remark the data points, the 'o' the cluster centers. Since this algorithm is an extension of the C-means algorithm (uses adaptive distance norm), it detects the elongated clusters. The orientation and shape can be "mined" from the eigenstructure of the covariance matrix: the directions of the axes are given by the eigenvectors. In Fig. 4.3 the contour-map shows the superposition of the four ellipsoidal clusters.

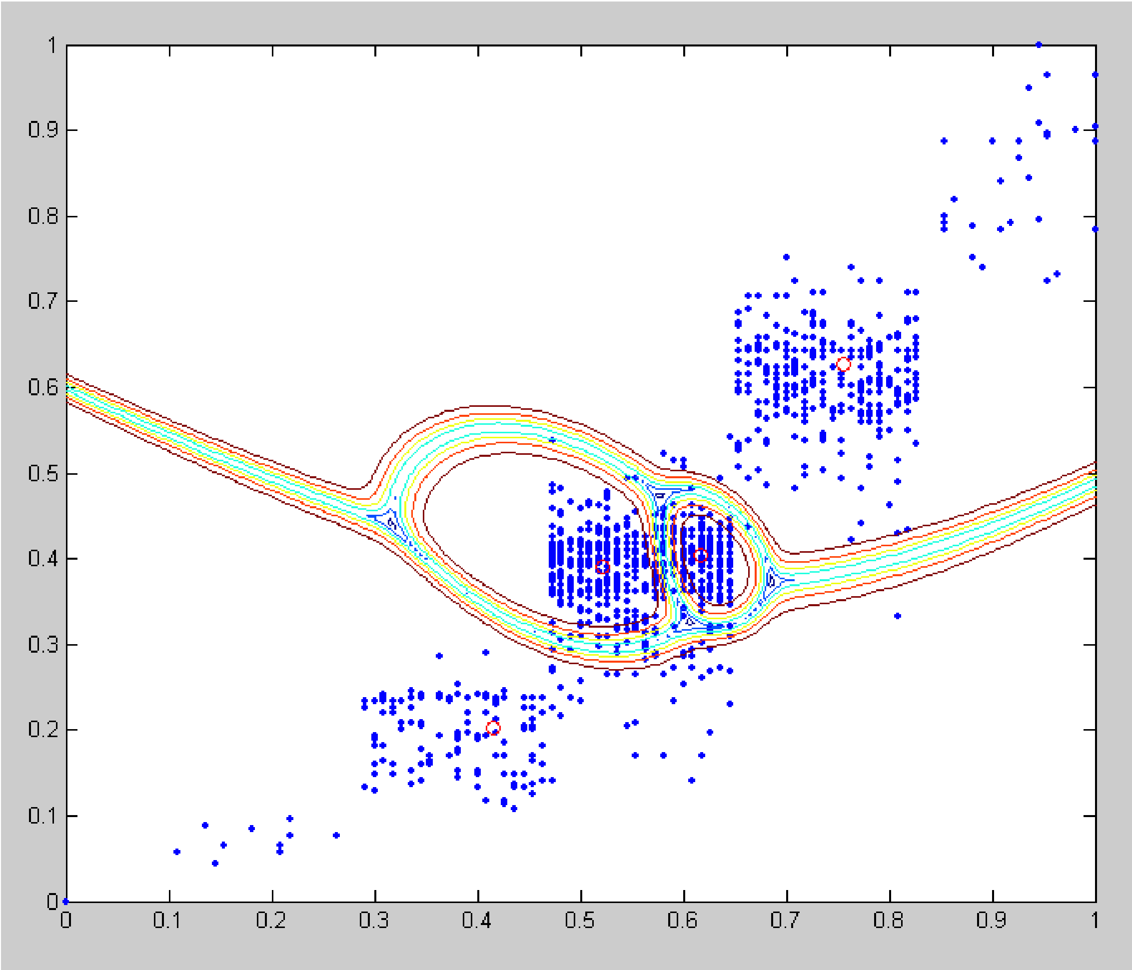
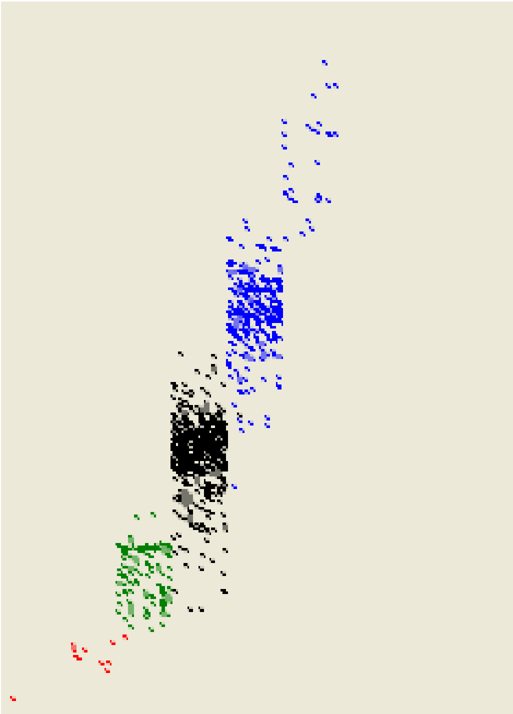


Figure 4.4: Result of Gath-Geva algorithm by the synthetic overlapping data with normalization.

In the figure 4.4 the '.' remark the data points, the 'o' the cluster centers. Cause of the exponential term in the distance norm, which decreases faster by increasing distance, the Gata-Geva algorithm divides the data space into disjoint subspaces shown in Fig. 4.4



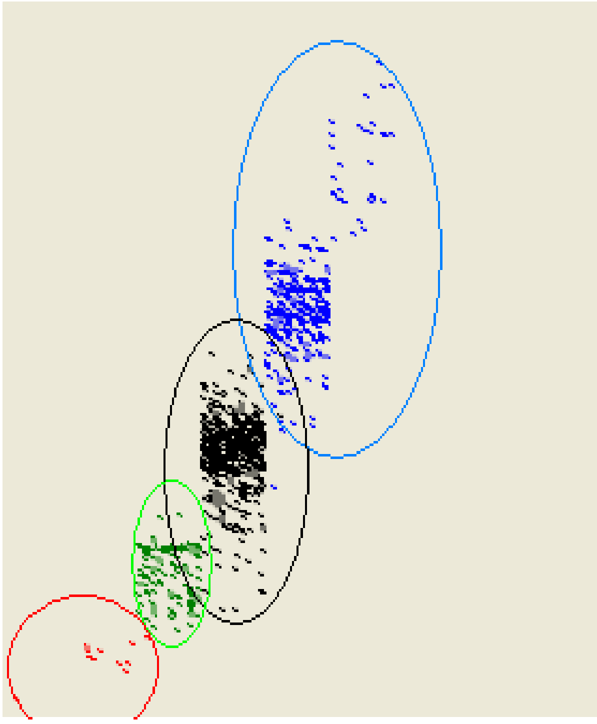


Figure 4.5: The display of data without regulating vector ellipse

Figure 4.6: The display of personnel total performance data with self regulating ellipse

Fig 4.5 displays distributions of personnel total performance data base on fuzzy c-mean algorithm. Finally software draws ellipse using regularity vector variables, result shown on Fig 4.6

Note that desired criteria may be implemented on choice.

4.2. RECEIVER OPERATING CHARACTERISTIC CURVE ANALYSIS

ROC graphs are another way in addition to confusion matrices to analyze the performance of classifiers. A ROC graph is a plot with the false positive rate on the X axis and the true positive rate on the Y axis. The point (0,1) is the perfect classifier because it classifies all positive cases and negative cases correctly. It is (0,1) because the false positive rate is 0 (none), and the true positive rate is 1 (all). The point (0,0) represents a classifier that predicts all cases to be negative, while the point (1,1) corresponds to a classifier that predicts every case to be positive. Point (1,0) is the classifier that is incorrect for all classifications.

In many cases, a classifier has a parameter that can be adjusted to increase TP at the cost of an increased FP or decrease FP at the cost of a decrease in TP. Each parameter setting provides a (FP, TP) pair and a series of such pairs can be used to plot an ROC curve. A non-parametric classifier is represented by a single ROC point, corresponding to its (FP,TP) pair. A ROC Curve yields also a rate between TP and FP. The rate of approaching the point (1,1) yields the performance of classification system. This means that, the more graph approaches to point (1,1) rapidly, the more system is successful in classification. In the following pages, ROC Curves of ANN, SVM and ANFIS will be indicated and performance analysis will be done as well.

4.2.1. ROC Curve Parameters

ROC Curve Analysis will be done depending on such parameters listed below:

TPR and FPR: True-Positive Rate and False-Positive Rate are the two axis: x and y; that are the actual class and the predicted class representers. Those terms are also used in confusion matrix terminology and it is so beneficial to learn them before analyzing the ROC Curve in latter sections. Firstly; as it is known that supervised learning is a machine learning technique for creating a function from training data and in artificial intelligence (AI) concept, a confusion matrix is an indicator that is generally used in supervised learning. Each column of the matrix represents the instances in a predicted class, while each row represents the instances in an actual class. It is beneficial for benchmarking two classes in a system. In fact, a confusion matrix contains information about actual and predicted class values done by a classification system. Performance of such systems is commonly evaluated using the data in the matrix. The following table indicates the confusion matrix for a two class classifier.

i) *a* is the number of **correct** predictions that an instance is **negative**,
ii) *b* is the number of **incorrect** predictions that an instance is **positive**,
iii) *c* is the number of **incorrect** of predictions that an instance **negative**,
iv) *d* is the number of **correct** predictions that an instance is **positive**.

		Predicted	
		Negative	Positive
Actual	Negative	**a**	**B**
	Positive	**c**	**D**

By using this confusion matrix, several attributes are used to analyze the performance of classification. Those are as follows:

i) **Accuracy (AC)** : is the proportion of the total number of predictions that were correct. It is determined by using the equation:

$$AC = \frac{a+d}{a+b+c+d}$$

ii) **True-Positive rate (TP)** : is the proportion of positive cases that were correctly identified, as calculated by using the equation:

$$TP = \frac{d}{c+d}$$

iii) **False-Positive rate (FP)** : is the proportion of negatives cases that were incorrectly classified as positive, as calculated by using the equation:

$$FP = \frac{b}{a+b}$$

iv) **True-Negative rate (TN)** : is defined as the proportion of negatives cases that were classified correctly, as calculated by using the equation:

$$TN = \frac{a}{a+b}$$

v) **False-Negative rate (FN) :** is the proportion of positives cases that were incorrectly classified as negative, as calculated by using the equation:

$$FN = \frac{c}{c+d}$$

vi) **Precision (P)** : is the proportion of the predicted positive cases that were correct, as calculated by using the equation:

$$P = \frac{d}{b+d}$$

According to this terminology, ROC Curve uses these two parameters as its axises and the ROC Curve shows the relationship between TP and FP axises and this yields the performance and accuracy of classification.

AUC :The area under the curve (AUC) is a measure of the ability of the diagnostic test to correctly identify cases. Diagnostic tests with higher AUCs are generally better and should always be higher than 0.5, indicating the test is better at diagnosing than chance. A hypothesis test is used to statistically test if the diagnostic test is better than chance at correctly diagnosing state. A significant p- value indicates the diagnostic test is better at diagnosing than chance.

SE: Standard error estimate under the area of ROC Curve. This shows the average deviation from the findings of ROC resulting data.

Confidence Interval: The criterion commonly used to measure the ranking quality of a classification algorithm is the area under the ROC curve (AUC). To handle it properly, it is important to determine an interval of confidence for its value. Confidence interval yields how the ROC curve is confidential with its results. Therefore, the higher confidence interval, the higher correctness in the results of classification.

4.2.2. ROC Curve Analysis (Fuzzy C-Mean)

The ROC Curve of Fuzzy c-means filter is as follows shown below:

Table 4.5: ROC Curve Analysis of Fuzzy c-means result

Test	Area	95% CI	SE	Z	p
Fuzzy c-means	0.58	0.46 to 0.70	0.062	1.29	0.983

As seen in Table 4.7 above, classes with their TPR and FPR and the area under the each step of TP and FP axises are handled with software. Area means that at each step, the distance between ROC Curve point and the diagonal line changes depending on the values of TP and FP values. Necessary values to benchmark Fuzzy C-mean with other filters are as follows with their values found by Fuzzy C-mean below:

i) **AUC:** 0,58

ii) **SE:** 0,062

iii) **Confidence Interval:** 0,46 to 0.70

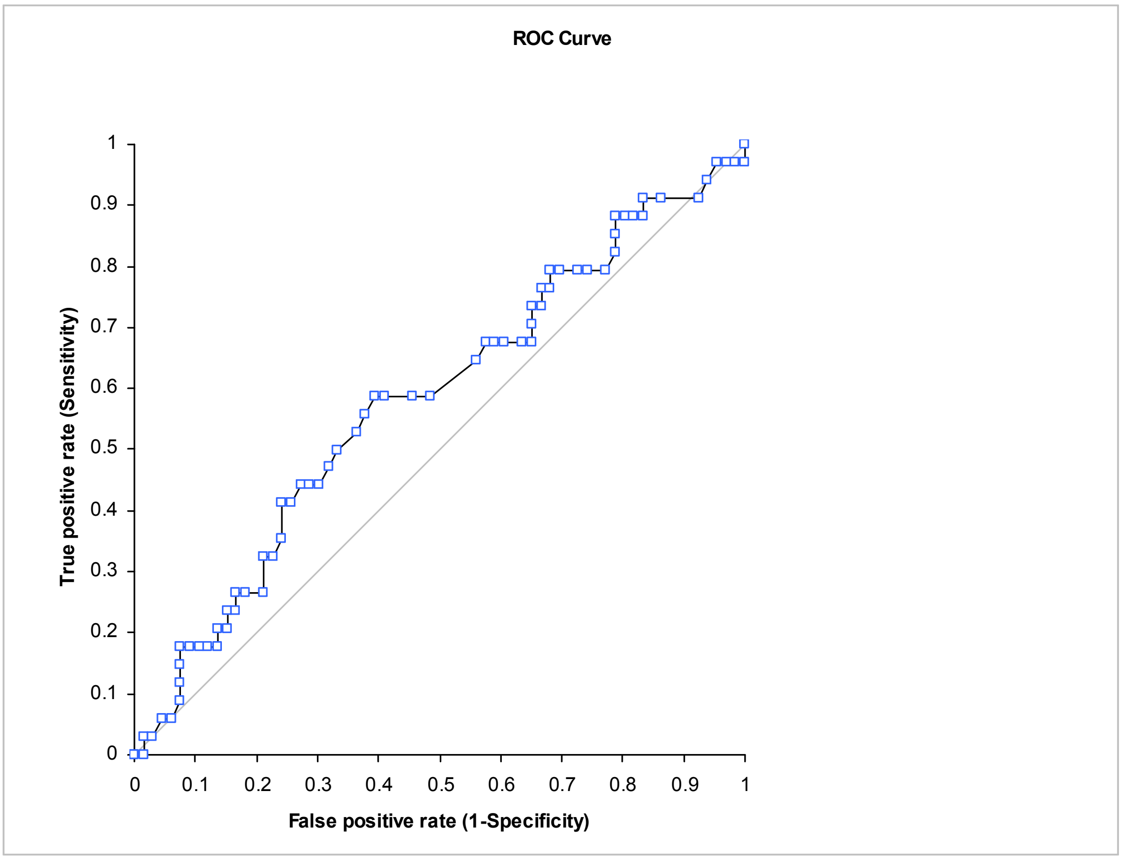


Figure 4.7: ROC Curve of Fuzzy C-Means

AUC is the total area under the curve and it means that how much less amount of AUC exist, then, the classification is more accurate and has more performance. AUC of Fuzzy C-mean is 0.58.

4.2.3. ROC Curve Analysis (Gustafson-Kessel)

Table 4.6: ROC Curve Analysis of Gustafson-Kessel Result

Test	Area	95% CI	SE	Z	P
Gustafson-Kessel	0.45	0.33 to 0.57	0.062	-0.84	0.7983

Table 4.6 displays Gustafson-Kessel algorithm ROC result. The less amount of AUC, the less amount of error in classification. The AUC for the test is 0.45. While p-value is 0.7983

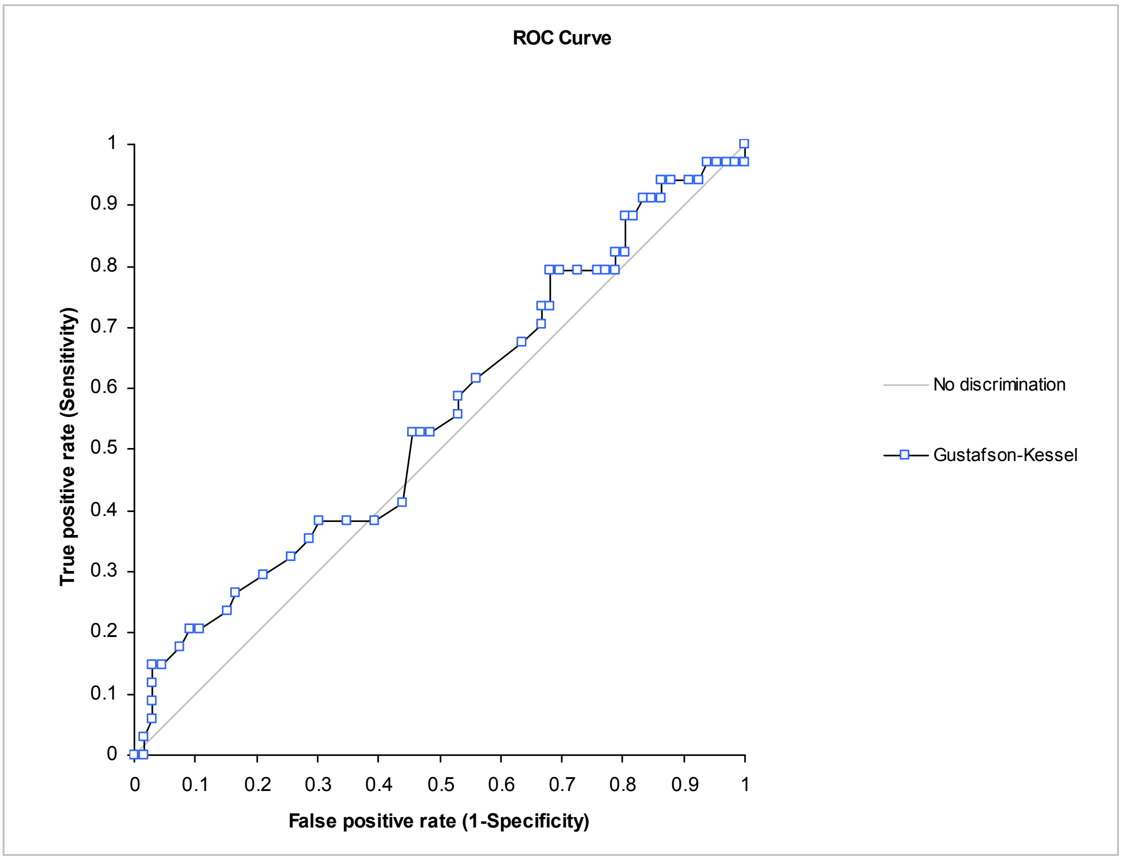


Figure 4.8: ROC Curve of Gustafson-Kessel

4.2.4. ROC Curve Analysis (Gath-Geva)

Table 4.7: ROC Curve Analysis of Gath-Geva Result

Test	Area	95% CI	SE	Z	p
Gath-Geva	0.42	0.30 to 0.54	0.061	-1.35	0.9121

In Table 4.7 shows Gath-Geva algorithm ROC result. The less amount of AUC, the less amount of error in classification. The AUC for the test is 0.42. While p-value is 0.9121

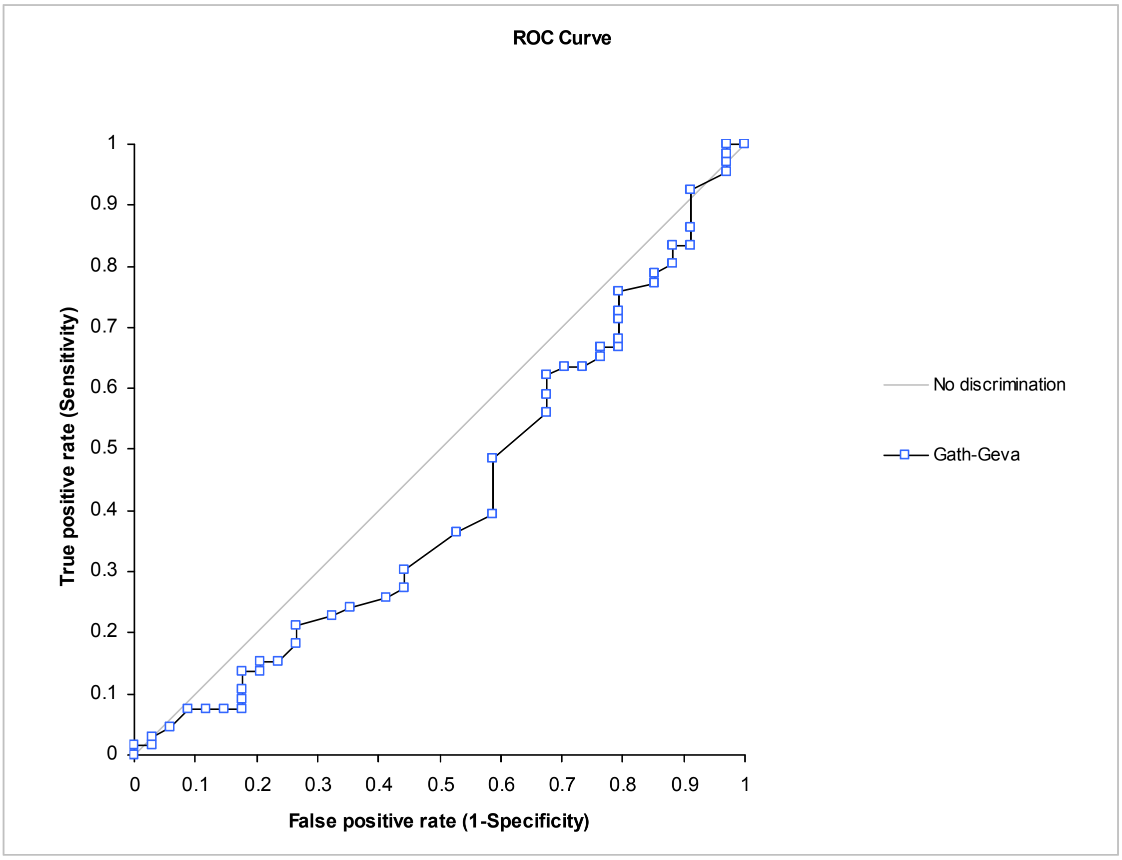


Figure 4.9: ROC Curve of Gath-Geva

Depending on this information the area under the curve for Fuzzy c-means is 0.58 and this value is greater than the critical value 0.5. the area for Gustafson-Kessel and Gath-

Geva are 0.45 and 0.42. These results reveal that, Fuzzy c-means display the best performance amount those three methods.

5. CONCLUSIONS

Online Self Regulating Clustering Method is applied to the human resource performance data, which are gathered from 1100 employees' yearly performance scores for two years.

The vital point in performance data evaluation is not gathering data and applying standard methods, but attaining concrete results through tailored to fit techniques for distinguishing among employees' performances. In this sense, Online Self Regulating Clustering Method yields optimum results to contribute in improving human resource management performance, and also hits bull's eye in promotion, bonus, and related fringe benefit decisions, thus maximize personnel motivation and corporate profitability.

In this study, upon given performance evaluation data gathered from a special firm's human resource management department, clustering analysis is run to figure out questions arising due to how to perceive and contrast different employee's performance evaluation results which are working at varying organizational units while those data are merely summarized as row score values. More importantly, when a perception of those data and comparison of different employee's performance data is on the focus for taking critical organizational decisions like, promotions, fringe benefit allotments, salary raises and so like, and an obstacle lies before the decision maker such that performance evaluation for every employee is undertaken concerning heavily the special requirements of each and every specific unit in the organization, a concrete tool to reconcile those performance evaluation scores with contrasting bases is of critical importance. Thus, clustering analysis as a reconciliation basis for contrasting employee performance evaluation data for critical decision making is of much assistance.

The result of the study utilizing clustering analysis on the data resulted in clustering our data in an optimum number of four different clusters. Such that, every cluster include qualitatively close performances while many of them stem from quantitatively diverse performance scores. Hence, a comparison among varying employees from diverse organizational units became probable upon statistically valid and justifiable foundations.

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