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A Combined Model of MCDM and Data Mining for Determining Question Weights in Scientific Exams

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Abstract

The existence of an appropriate system for assessing educational development is a key issue in achieving the pre-determined educational goals. The abundance of papers in recent years which investigate the necessity and adequacy of evaluation corroborate this matter. In order to increase the precision of the assessment process of students' educational development, the present study tries to propose a combined method of crisp and fuzzy inputs in which multi-criteria decision making and data mining techniques are used. This method is a combined model of PROMETHEE and fuzzy analytic network process to determine question weights in the scientific examinations considering difficulty, complexity and importance of each question. In this model, data mining is applied for improving the model's inputs.

Keywords: Assessing students; Fuzzy analytic network process; Preference function; PROMETHEE; Multi-criteria decision making; Data mining

1. Introduction

Evaluating educational development is a very important and applicable process in any educational system. For instance, it can be used to measure the rate of students' success in learning and teachers' success in teaching. Although teachers have paid much attention to this process of transforming qualitative variables to quantitative ones, there has been skepticism about its precision. These kinds of exams are not decisive due to their nature. since humanities are not exact sciences; their results are not decisive by nature. Moreover, a highly qualified evaluation system paves the ground for individual enhancement and ensures fair ranking and scoring for all the students. Thus, assessment systems have to be not only logical and transparent but also easily-implementable on computers. So, it seems that Fuzzy Analytic Network Process (FANP) is suitable for designing such a system due to its capabilities in implementation on computers and its uncertain inputs. In addition, PROMETHEE is a method which has recently attracted much attention because of its mathematical properties and easy application. Data mining approach is also a new interdisciplinary and developing approach which tries to extract hidden knowledge and information from a substantial amount of data. Therefore, it can be used effectively in analyzing the data obtained from the exams with a large number of questions and test-takers. Also, the theory of fuzzy sets since its introduction in 1965 by Professor Lotfi Zadeh [12] has been widely used for problem solving in different science fields. Recently, this theory has been used for educational assessment and ranking.

Biswas presented a fuzzy method for educational assessment in 1995 [5]. In 1999, Chen & Lee also introduced a fuzzy method for solving the problem of ranking students who receive the same score using the Biswas method [6]. For transforming traditional scores to rankings, Echaus & Vachtsevanos (1995) offered a fuzzy logic system [7]. Law (1996) proposed a fuzzy-structured model which was an educational ranking system and aggregated the scores of different exams in order to produce one specific score for each student [8].

Wilson & Karr & Freeman (1998) presented an automatic ranking system based on fuzzy rules and genetic algorithm [9]. Ma & Zhou (2000) presented a fuzzy set approach for investigating the students' learning outcomes using the assessment of their peers and teachers [10]. Wang & Chen (2008) proposed a method for assessing students' answer sheets using fuzzy numbers associated with the degrees of rater reliability [4].

It can be found from the previous research that fuzzy numbers, fuzzy logic systems and fuzzy rules have been used in different educational ranking systems. Weon & Kim (2001) improved an assessment strategy which was based on fuzzy Membership Functions (MF). In this method, they emphasized three important factors of questions in their assessment including questions' difficulty, complexity and importanc [11]. Bai & Chen (2008 a) presented a method to automatically construct the ranking MFs of fuzzy rules for assessing students' educational development [2]. Additionally, Bai & Chen (2008 b) applied a method for using fuzzy MFs and fuzzy rules for a similar purpose. To overcome subjectivity problem of the difficulty factor in the Weon and Kim method (2001), they considered difficulty as a function of answer accuracy and the spent time for answering each question [3]. However, their method still suffered from the subjectivity problem since the obtained results were largely dependent on the weights specific to the factors which were determined by the subjective knowledge of domain experts. Ibrahim Saleh & Seong in Kim (2009) proposed an improved alternative of the Bai & Chen method which presented a fuzzy logic system for considering the questions' difficulty, complexity and importance based on the Mamdani's fuzzy inference (Mamdani, 1974) and the Center of Gravity (COG) defuzzification [1].

Their method was also defective in application since measuring the answering time for each question is a main problem in the integrated exams and the exams with a large number of questions.

In these similarly conducted studies, there has been an attempt to adjust the initial question weights while the accuracy and precision of determining the weights are still under question. Thus, in this paper, a new method is presented for determining question weights by considering the factors of question difficulty, importance and complexity and implementing a combined method of PROMETHEE and fuzzy analytic network process using a data mining approach.

The paper is organized as follows: in Section 2, a detailed review of the proposed model is made. In Section 3, a case study is presented which was conducted at the Islamic Azad University of Qazvin. Section 4 includes the comparisons and conclusions and Section 5 presents some recommendations for future works. Section 6 is the reference section.

2. A Review of the Combined Model of PROMETHEE and Fuzzy Analytic Network Process using Data Mining Approach

One of the main reasons for using fuzzy logic in humanities is to investigate and analyze the current mental complexities in such sciences. Also, as is evident from the name of ANP, the important capability of this method is in analyzing the internal relationships of the processes in order to compare and rank various alternatives. Therefore, combining these two different fields can be instrumental in humanities. Moreover, pairwise comparisons of the alternatives leading to the FANP inputs can be achieved more accurately using PROMETHEE.

2.1. Fuzzy Sets Theory

In 1965, Professor Lotfi Zadeh introduced fuzzy sets theory for the first time and made the arrangements for modeling vague information and approximate reasoning with mathematical equations, which was a great transformation in mathematics and classical logic. In this regard, the concept of membership function is of special importance in fuzzy sets theory since all the information regarding a fuzzy set is described by a membership function and used in all its applications and theoretical issues. There are different ways to define membership function in the literature of fuzzy sets. The membership function used in this study is the triangular type. Furthermore, in order to make fuzzy comparisons between different alternatives, fuzzy operators are exposed on the fuzzy numbers.

There is a difference between using fuzzy information in decision making, calculations , modeling and implementing fuzzy results in the real world. So, fuzzy numbers need to be converted to crisp numbers. In order to convert a fuzzy number to a crisp number, there are different methods like α cut, MOM, COG and so on. In this paper, Center of Gravity (COG) defuzzification was used.

2.2. Fuzzy Analytic Network Process

ANP[1] is a comprehensive approach in decision making which has been obtained by generalizing the hierarchy to the network. Although AHP[2] technique removes basic measurement defects, it does not measure the dependency between the criteria. AHP

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[1] Analytical Network Process

[2] Analytic hierarchy Process

assumes that the presented criteria in hierarchical structures are independent from each other, which is not always acceptable. Therefore, ANP also considers dependency and feedback. In this method, pairwise comparisons are made among the judgments which use crisp numerical values in the scale of 1 to 9. ANP results convert multi-dimensional scales of measurement to single-dimensional scales of priority.
This process includes the following steps:

1. Problem definition and modeling
2. Forming pairwise comparison matrices and priority vectors and calculating incompatibility rate of each matrix
3. Forming super-matrices
4. Extracting priorities from super-matrices and concluding

Furthermore, sometimes it seems impossible or unrealistic to obtain accurate judgments for pairwise comparisons due to the nature of human judgment, situational complexity and uncertainty involvement. Thus, accepting some causes of

ambiguity in the complex decision making about real numbers is inevitable; however, such kinds of ambiguities are resolvable in fuzzy sets theory.
The concept of fuzziness is applied in ANP and AHP in an indirect way and without using fuzzy sets. But, researchers have generalized them and proposed some methods in which fuzzy numbers are used for demonstrating the elements' preference rate. In this paper, at first, a method is used to define the pairwise comparison matrices in the form of triangular fuzzy numbers in order to determine incompatibility rate and conduct the following ANP calculations; then COG method is used for defuzzification. After that, the rest of the steps are followed according to the ANP method.

2.3. PROMETHEE[1]

This method which was presented by Burns et al. (1986) is one of the ranking methods for solving multi criteria problems. The eye-catching success of PROMETHEE in different methods is essentially due to its mathematical properties and easy application. In this method, preference function is used for ranking after the priority relationship is created. This method is used in the present study to create part of the inputs of fuzzy analytic network process.

2.4. Data Mining

Data mining is an inter-disciplinary and rapidly growing approach in which the extraction and analysis of a large amount of data are done for discovering meaningful rules and paradigms. Data mining techniques are divided into descriptive and predictive categories. Some examples of these methods include modeling for prediction, clustering, dependency modeling, summarizing, associating or confidence and so on. In this paper, clustering is used for improving PROMETHEE inputs.

Cluster Analysis:

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[1] Preference Ranking Organization Method for Enrichment Evaluations

The main issue in clustering is to distribute inputs among K different groups in such a way that each group's data are similar and different groups' data are different. In fact, the concentration is on the number of things which are similar in order to discover their similarities and to be able to discover their behaviors and make decisions based on the identification.
The main approaches in clustering include partitioning methods, hierarchical methods, density-based methods, grid based methods and SOM. In this paper, a partitioning method called K-Means is used for clustering the students.

2.5. The Proposed Combined Method

As mentioned above, the steps followed in fuzzy analytic network process are the same as the ones followed in ANP except that, in the second step, i.e. forming a pairwise comparison matrix, the fuzzy inputs are used at first and then they are defuzzified for calculating the incompatibility rate and being used by FANP. Here, Super Decision Software is used for conducting the calculations related to Steps 3 and 4. This software was designed by Bill Adams solely for ANP calculations and was confirmed by Mr. Thomas L. Saati.

2.5.1. Problem Definition and Forming Model:

The current issue is to analyze exam questions for determining their weights in investigating the students' exam papers, the so-called question weights. This issue has been done by considering questions' difficulty, importance and complexity factors which are named criteria in designing problem models. The exam questions are treated as alternatives in the decision making process and, finally, the devoted weights determine the goal of the problem which is finding the question weights.

2.5.2. Forming Pairwise Comparison Matrices

In this network, the required pairwise comparison matrices include pairwise comparison matrices of the elements of the cluster of questions with respect to each element of the cluster of criteria; pairwise comparison matrices of the elements of the cluster of criteria with respect to each element of the cluster of criteria; pairwise comparison matrices of the elements of the cluster of criteria with respect to each element of the cluster of questions; pairwise comparison matrices of the elements of the cluster of questions with respect to each element of the cluster of questions; pairwise comparison matrices of the clusters with respect to the cluster of questions and pairwise comparison matrices of the clusters with respect to the cluster of criteria.

2.5.3. *Creating Fuzzy Numbers and Forming Fuzzy Pairwise Comparison Matrices*

Paired Comparison Matrix of the Elements of the Cluster of Questions with respect to Difficulty Element:
To this end and in order to use the available real data, the information related to the students' answer accuracy rate to the questions is gathered. Then, the obtained data go through the following steps and lead to the pairwise comparison matrix of the elements of the cluster of questions with respect to the difficulty element.
Step 1: Pre-processing the data: In this step, the available data are initially investigated so that incomplete and noisy data will be modified or removed.

Step 2: Mining the data: In this step, the information obtained from the previous step goes through clustering algorithm and lead to the placement of each student in a cluster.
Step 3: Interpreting the discovered knowledge: In this step, first, the average accuracy rate of each question is calculated in each cluster. Then, using Relation 1, the triangular fuzzy number related to the accuracy rate of each question is formed:

$$D_j = (L_j, M_j, U_j)$$
$$\begin{cases} L_j = \min(a_{ij}) \\ M_j = (1/n)\left(\sum_{i=1}^{n} a_{ij}\right) \\ U_j = \max(a_{ij}) \end{cases} \qquad (1)$$

a_{ij} denotes the mean accuracy rate of Cluster i on question j.

If *a* and *b* are two alternatives for comparison, then the preference rate of *a* in relation to *b*, considering the criteria k which is shown by $P_k(a\ ,b)$, is a function of their score difference in the criteria k.

$$\forall a,b \in A \quad P_k(a\ ,b) = F_k[(d_k(a,b)]$$
$$d_k(a,b) = g_k(a) - g_k(b) \qquad (2)$$

Also, in the criteria with the negative nature which should be minimized, the preference function is shown in the following way:

$$\forall a,b \in A \quad P_k(a\ ,b) = F_k[(-d_k(a,b)] \qquad (3)$$

Preference functions can be in different forms. In this paper, the exponential preference function which is shown in the following way is used. The differences is that, for the states with the deviation about zero, the preference function should be about one and for the state with extremely preference, the preference function should be about nine.

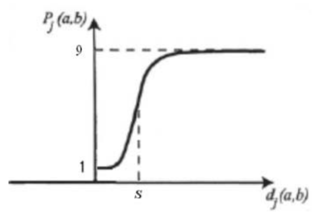

Figure 1: Exponential Preference Function

The preference function is defined separately in this paper for positive and negative criteria:

For positive criteria:

$$P_k(a\ ,b) = \begin{cases} 1 - e\text{^}(-(d+t)\text{^}2)/(2*s\text{^}2))*9 & d > 0 \\ 1/P_k(b\ ,a) & d < 0 \end{cases} \quad (4)$$

For negative criteria:

$$(5) \quad \begin{cases} 1 - e\text{^}(-(-d+t)\text{^}2)/(2*s\text{^}2))*9 & d < 0 \quad P_k(a\ ,b) = \\ 1/P_k(b\ ,a) & d < 0 \end{cases}$$

In the above relations, the parameter *s* is defined as the middle value between the indifference threshold (the largest deviation which is ignored by the decision maker) and preference threshold (the smallest deviation which suffices for the complete preference). Moreover, to adjust and balance the relation, parameter *t* is in a way that, in the indifference state, the preference function equals one. This value changes in proportion to the value of parameter *s*, according to the following Table. The confirmed value is compared in order to be used by deviation average.

t	0.024	0.048	0.073	0.097	0.121	0.146	0.170	0.194	0.218
s	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45

Table 1: Different values of Parameter *t* for each corresponding value of parameter*s*

In the pairwise comparison matrix of the elements of the cluster of questions with respect to the difficulty element, the second type preference function is used due to the questions' accuracy rate which has a negative effect on the question difficulty and, as a result, on the devoted score to the answer. The main effective parameter in the deviations' preference function is the rate of question accuracy (d). This parameter goes under the preference function for each of the up, down and middle limits of the triangular fuzzy numbers which are derived from the subtraction of the triangular fuzzy numbers corresponding to each question's accuracy rate. The result of this calculation is the triangular fuzzy number which indicates the preference of two compared questions with respect to the difficulty element.

This fuzzy number need to be calculated for each opposite pair; if, in a state, one of the parameters of the triangular fuzzy numbers had a positive accuracy rate of deviation, the optimum fuzzy number could be obtained by reversing the preference rate of the opposite state.

Pairwise Comparison Matrices of the Elements of the Cluster of Questions with respect to the Complexity Element:

In this section, fuzzy terms are used for the pairwise comparison of the elements. Thus, the expert views are turned into triangular fuzzy numbers considering the fuzzy terms' definition. Therefore, expert views are considered in a crisp scale corresponding to the following table. Then, using a similar method, which was used in forming the initial fuzzy numbers of the answers' accuracy rate for making the pairwise comparison matrix,

the triangular fuzzy numbers are constructed for the pairwise comparison matrix.
If $D_j = (L_j, M_j, U_j)$ and $D_i = (L_i, M_i, U_i)$, then:

$$D_i - D_j = (L_i - U_j, M_i - M_j, U_i - L_j) \qquad (6)$$

Crisp values	fuzzy terms
9	Extremely
7	Very Strongly
5	Strongly
3	Moderately
1	Equally

Table 2: Crisp values corresponding to fuzzy terms

$$C_{j,k} = (L_{j,k}, M_{j,k}, U_{j,k})$$
$$\begin{cases} L_{j,k} = \min(C_{i,j,k}) \\ M_{j,k} = \left(\sqrt[n]{\prod_i c_{ijk}}\right) \\ U_{j,k} = \max(C_{i,j,k}) \end{cases} \qquad (7)$$

Where c_{ijk} indicates the crisp preference value of the question *j* to the question *i* according to the k^{th} expert view.
This method is used for forming other matrices as well.

2.5.4. Defuzzifying the Numbers - Forming Crisp Pairwise Comparison Matrix - Calculating Incompatibility Rate:
To defuzzify the triangular fuzzy numbers obtained from the previous section, the Center of Gravity (COG) defuzzification is used. In this paper, in order to increase defuzzification calculation rate and accuracy, the pseudo-code of the MATLAB Software is being applied. In this pseudo-code, inputs and outputs are in EXCELL Software. The compatibility rate of each and every crisp judgment matrix obtained in the previous section and the preference vector corresponding to each matrix can be calculated by Super Decisions Software.

```
clear all
fuzzy=xlsread('book1.xlsx')
x=0:0.1:10
for i=1:size(fuzzy,1)
    mf=trimf(x,[fuzzy(i,1) fuzzy(i,2) fuzzy(i,3)])
    fuzzy(i,4)=defuzz(x,mf,'centroid')
end
xlswrite('centroid.xlsx',fuzzy)
```

"the pseudo-code of the MATLAB Software for defuzzification"

2.5.5. Forming a Super-matrix:
Using the obtained weights from Section 2.5.4., an inharmonious super-matrix is formed. This super-matrix may be inharmonious, i.e. the sum of its columns' components is not one. Thus, the inharmonious super-matrix should be turned to a harmonious super-matrix. To obtain a harmonious super-matrix, at first, the cluster matrix should be formed. Then, through multiplying the corresponding components in the cluster matrix by the ones in the inharmonious matrix, a harmonious matrix will be obtained. By combining pairwise comparison matrices of the clusters, with respect to the cluster of questions, with the pairwise comparison matrices of the clusters, with respect to the cluster of criteria, the cluster matrix is obtained.

Forming a Limited Super-matrix:
The obtained super-matrix does not give fixed and single weights for the elements. Therefore, the super-matrix should be raised to the power of k+1 (in which k is large enough to give single weights for each and every element). This process can be followed in Super Decisions Software.

2.5.6. Extracting Priorities from the Super-matrix and Concluding:
After forming the limited super-matrix and elements of the clusters of alternatives and criteria in the manner explained above, they will obtain fixed corresponding weights. These weights are the final weight of these elements for making a decision. To convert the weights produced from the super-matrix to question scores, these weights should be commensurated considering the exam's required scale. To this end, the following relation is used:

$$g_i = w_i \times (S / \sum_{i=1}^{m} w_i) \qquad (8)$$

g_i Denotes the assigned score of question

3. A Case Study Conducted at Qazvin Islamic Azad University

In this case study, the results of the Mechanic Assembling course for mechanical engineering students was investigated. This exam included 11 questions and 91 students took part in it. The initial results of data gathering are presented in Appendix 1.

3.1. Data Mining

3.1.1. Pre-processing the Data:
In this step, it was evident, according to Appendix 1, that students 178, 88 and 106 do not have any scores for questions 8, 7 and 4, respectively. To investigate this issue, the sum of each student's scores were calculated and after being compared with the devoted scores, it was found out that the above-mentioned scores were zero. Therefore, there was no need to remove the (student) samples in which the above lost data were located.

3.1.2. Pareto Analysis and Determining the Number of Clusters (K):
In this step, the sum of the accuracy rates obtained by students was Pareto analyzed in a traditional way. And the number of created categories by MINITAB was considered as

the number of clusters in the K-Means algorithm. The results showed that the number of clusters should be k times as large as 7 in this study.

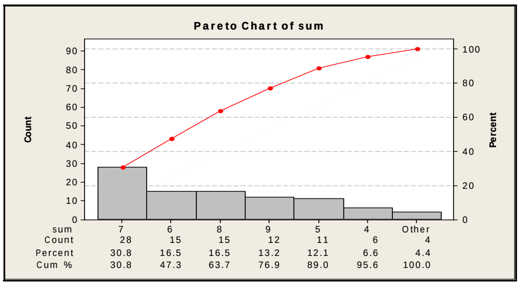

Figure 2: Pareto analysis for determining the number of clusters

3.1.3. Clustering

As mentioned before, the K-Means algorithm was used in this paper for clustering. To increase the calculation accuracy and speed, MINITAB software can also be used.

3.1.4. Calculating the Averages and Forming Triangular Fuzzy Numbers of Accuracy Rate:

In this step, first the average of each question's accuracy rate was calculated in each cluster; then in order to form a triangular fuzzy number suitable for the accuracy rate of each question, the average, maximum and minimum numbers obtained for the clusters were considered. The results for this step are mentioned in Table 3. In this table, the component 1-1 indicates the average of accuracy rate for question 1 in cluster 1. The last three rows show triangular fuzzy numbers which are in proportion with each question's accuracy rate (x: A , B , C).

11	**10**	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**	**Q.N**
											Cluster
65	*57*	*65*	*69*	*78*	*93*	*80*	*26*	*64*	*39*	*58*	**1**
42	*65*	*23*	*11*	*11*	*36*	*71*	*80*	*46*	*38*	*26*	**2**
67	*61*	*22*	*20*	*49*	*75*	*60*	*77*	*62*	*30*	*65*	**3**
70	*68*	*89*	*66*	*86*	*91*	*73*	*88*	*81*	*59*	*61*	**4**
66	*57*	*93*	*47*	*65*	*79*	*8*	*58*	*56*	*12*	*28*	**5**
65	*43*	*53*	*41*	*54*	*71*	*62*	*73*	*92*	*34*	*53*	**6**
43	*40*	*73*	*7*	*0*	*83*	*65*	*83*	*60*	*84*	*60*	**7**
42	*40*	*22*	*7*	*0*	*36*	*8*	*26*	*46*	*12*	*26*	**A**
59	*56*	*60*	*37*	*49*	*75*	*60*	*69*	*66*	*42*	*50*	**B**
70	*68*	*93*	*69*	*86*	*93*	*80*	*88*	*92*	*84*	*65*	**C**

Table 3: Calculating the averages and forming triangular fuzzy numbers in proportion with each question's accuracy rate (%)

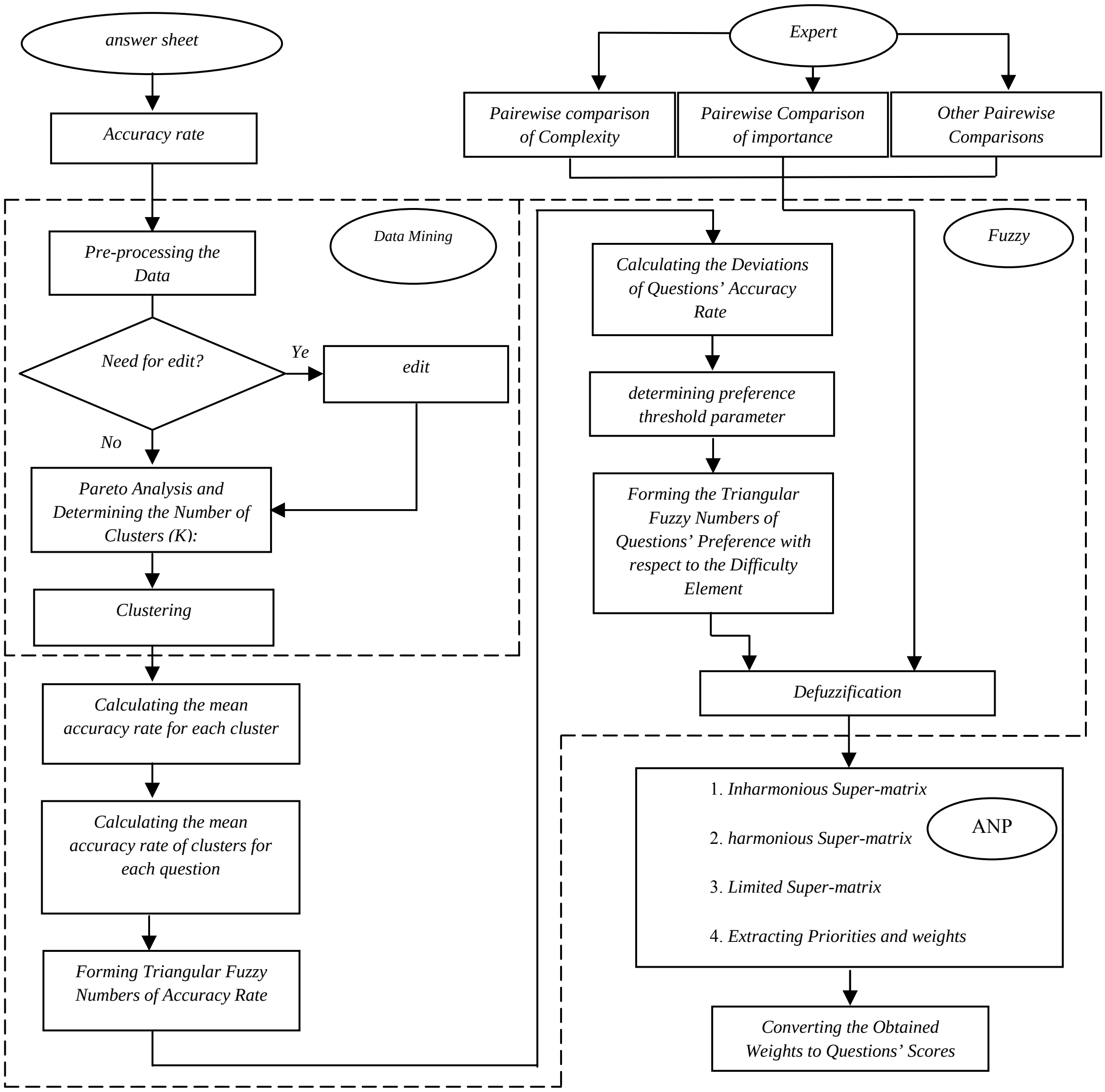

Figure 3: General view of the proposed model

3.2. Forming Pairwise Comparison Matrices

3.2.1. Calculating the Degree of Questions' Preference with respect to Difficulty Element using PROMETHEE

3.2.1.1. *Calculating the Deviations of Questions' Accuracy Rate*

In this step, all the deviations of the possible pairs of triangular fuzzy numbers, which were obtained from Section 3.1.4., were calculated using Relation 6. For example, to calculate the accuracy rate deviation of question 1 from question 2, the following steps should be followed according to the results obtained from Section 3.1.3. and Relation 6:

A.r.1 (26%,50%,65%)
A.r.2 (12%,42%,84%)
A.r.1 – A.r.2 = (26% - 84% , 50% - 42% , 65% - 12%)
A.r.1 – A.r.2 = (- 58% , 8% , 53%)

3.2.1.2. Forming the Triangular Fuzzy Numbers of Questions' Preference with respect to the Difficulty Element

In order to determine the rate of question preference with respect to the difficulty element, the exponential preference function presented in Relation 5 was used taking into account that the accuracy rate of each question is in a reverse relationship with that question's difficulty. It is worth mentioning that for determining preference threshold parameter (s), the middle limit average of triangular fuzzy numbers were used, which were obtained in Section 3.2.1.1.; thus here S=0.1. This relation was calculated for each of the three up, down and middle limits of triangular fuzzy numbers related to the accuracy rate deviation. If one of these limits was positive, the preference rate would be calculated by reversing the opposite value. For instance,

A.r.1 – A.r.2 = (d1 , d2 , d3) =(- 58% , 8% , 53%)

S=0.1 , t=0.048

P(1,2)=(a , b , c)

*c = 1-e^(-((-d1+t)^2)/(2*s^2)))*9 =9*

*b= 1/ (1-e^(-((d2+t)^2)/(2*s^2))*9) =0.2*

*a=1/ (1-e^(-((d3+t)^2)/(2*s^2))*9) =0.11*

3.2.1.3. Defuzzification and Forming Pairwise Comparison Matrix of Question Preference with respect to the Difficulty Element

In this step, the triangular fuzzy numbers, obtained from Section 3.2.1.2., were turned to deffuzzified inputs required for the Super Decision Software and changed into crisp numbers. As mentioned above, the Center of Gravity (COG) defuzzification is one of the most accurate methods and it was used in this paper. Also, to reduce the required calculation time and its errors, the pseudo-codes mentioned in Section 2.5.4., were used in MATLAB Software.

As mentioned in section 2.5.3 about preference function, for the states with the deviation about zero, the preference should be about one. This state occurs often when calculating deviations of a question from itself (for instance preference of question 1 from question 1). To this end all the deffizified numbers should be so-scaled. Here by a simple proportion, all defuzzified numbers are divided to 3.369. Preference calculations for questions 1 and 2 are shown in table 4 and the final results are presented in Table 5.

$P_k(1\ ,2) = 1/P_k(2\ ,1) = 1/1.402 = 0.71$

j	i	Li	Mi	Ui	Lj	Mj	Uj	Lij	Mij	Uij	PROMETHEE			Defuzzy	final	status
2	1	26%	50%	65%	12%	42%	84%	-58%	8%	53%	9.00	0.20	0.11	3.1	0.920	×
3	1	26%	50%	65%	46%	66%	92%	-66%	-16%	19%	9.00	7.98	0.12	5.699	1.691	√
4	1	26%	50%	65%	26%	69%	88%	-62%	-19%	39%	9.00	8.48	0.11	5.862	1.740	√
5	1	26%	50%	65%	8%	60%	80%	-54%	-10%	57%	9.00	6.01	0.11	5.039	1.496	√
6	1	26%	50%	65%	36%	75%	93%	-67%	-25%	29%	9.00	8.90	0.11	6.003	1.782	√
7	1	26%	50%	65%	0%	49%	86%	-60%	1%	65%	9.00	0.71	0.11	3.273	0.971	×
8	1	26%	50%	65%	7%	37%	69%	-43%	13%	58%	9.00	0.14	0.11	3.1	0.920	×
9	1	26%	50%	65%	22%	60%	93%	-67%	-10%	43%	9.00	6.01	0.11	5.039	1.496	√
10	1	26%	50%	65%	40%	56%	68%	-42%	-6%	25%	9.00	4.00	0.11	4.369	1.297	√
11	1	26%	50%	65%	42%	59%	70%	-44%	-9%	23%	9.00	5.55	0.11	4.886	1.450	√

12%	42%	84%	26%	50%	65%	-53%	-8%	58%	9.00	5.06	0.11	4.723	1.402	√
12%	42%	84%	12%	42%	84%	-72%	0%	72%	9.00	1.00	0.11	3.369	1.000	√
12%	42%	84%	46%	66%	92%	-80%	-24%	38%	9.00	8.86	0.11	5.984	1.776	√
12%	42%	84%	26%	69%	88%	-76%	-27%	58%	9.00	8.94	0.11	6.003	1.782	√
12%	42%	84%	8%	60%	80%	-68%	-18%	76%	9.00	8.34	0.11	5.8154	1.726	√
12%	42%	84%	36%	75%	93%	-81%	-33%	48%	9.00	8.99	0.11	6.003	1.782	√
12%	42%	84%	0%	49%	86%	-74%	-7%	84%	9.00	4.54	0.11	4.549	1.350	√
12%	42%	84%	7%	37%	69%	-57%	5%	77%	9.00	0.29	0.11	3.133	0.930	×
12%	42%	84%	22%	60%	93%	-81%	-18%	62%	9.00	8.34	0.11	5.815	1.726	√
12%	42%	84%	40%	56%	68%	-56%	-14%	44%	9.00	7.48	0.11	5.529	1.641	√
12%	42%	84%	42%	59%	70%	-58%	-17%	42%	9.00	8.17	0.11	5.759	1.709	√

Table 4: preference calculations for questions 1 and 2

Difficulty	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*
1	0.713	1.691	1.740	1.496	1.782	0.959	0.62	1.496	1.297	1.450
2		1.776	1.782	1.726	1.782	1.350	0.804	1.726	1.641	1.709
3			1.138	0.770	1.450	0.590	0.560	0.770	0.670	0.740
4				0.69	1.297	0.570	0.560	0.690	0.620	0.670
5					1.668	0.650	0.560	1	0.840	0.960
6						0.560	0.560	0.600	0.570	0.590
7							0.630	1.538	1.350	1.496
8								1.772	1.740	1.767
9									0.840	0.960

10	1. 1 3 6

Table 5: Pairwise comparison matrix of the elements of the cluster of questions with respect to the difficulty element

Importance	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*
1	7	7	7	7	7	7	7	7	3	1/3
2		1/3	1	1	1/3	1/3	1/5	1/3	1/7	1/9
3			3	3	1	1	1	1	1/3	1/5
4				1	1/3	1/3	1/5	1/5	1/7	1/9
5					1/3	1/3	1/3	1/3	1/5	1/7
6						1	1	1	1/5	1/5
7							1	1	1/5	1/5
8								1	1/5	1/7
9									1/3	1/5
10										1/3

Table 6: Pairwise comparison

matrices of the elements of the cluster of questions with respect to the elements of complexity and importance

3.2.2. Forming the Pairwise Comparison Matrix of Questions' Preference with respect to the Elements of Complexity and Importance

To form the above matrices, expert views were used according to the explanations mentioned in Section 2.6.2., which are presented in Table 6.

3.2.3. Forming Other Pairwise Comparison Matrices

To form these matrices, we follow the way mentioned in section 3.2.2.

3.3. Analytic Network Process (ANP)

All the calculations of this section were conducted using Super Decisions software which was confirmed by Mr. Thomas L. Saati.

3.3.1. Inharmonious Super-matrix

3.3.2. Cluster-matrix

3.3.3. Harmonious Super-matrix

Harmonious matrix was obtained by multiplying each component of cluster matrix by the corresponding component of inharmonious matrix.

3.3.4. Limited Super-matrix

The resulted super-matrix does not lead to single and fixed weights. Thus, the super-matrix should be raised to the power of k+1 (in which k is a large enough number to give single weights for each and every element).

	accuracy	Complexity	Importance	1	2	3	4	5	6	7	8	9	10	11
accuracy	0.00	0.17	0.50	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18
Complexity	0.25	0.00	0.50	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
Importance	0.75	0.83	0.00	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75
1	0.20	0.11	0.26	0.00	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.14	0.12
2	0.02	0.13	0.02	0.11	0.00	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.08	0.11
3	0.05	0.07	0.05	0.05	0.10	0.00	0.10	0.10	0.10	0.10	0.10	0.10	0.04	0.04
4	0.02	0.06	0.02	0.14	0.10	0.10	0.00	0.10	0.10	0.10	0.10	0.10	0.12	0.13
5	0.02	0.08	0.02	0.07	0.10	0.10	0.10	0.00	0.10	0.10	0.10	0.10	0.09	0.07
6	0.05	0.06	0.05	0.11	0.10	0.10	0.10	0.10	0.00	0.10	0.10	0.10	0.11	0.09
7	0.05	0.11	0.05	0.09	0.10	0.10	0.10	0.10	0.10	0.00	0.10	0.10	0.09	0.08
8	0.07	0.14	0.05	0.19	0.10	0.10	0.10	0.10	0.10	0.10	0.00	0.10	0.21	0.17
9	0.05	0.08	0.05	0.08	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.00	0.08	0.07
10	0.20	0.09	0.14	0.11	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.00	0.11
11	0.28	0.08	0.29	0.05	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.04	0.00

Table 7: Inharmonious super-matrix

Cluster Name	Question	Criteria
Question	***0.75***	***0.5***
Criteria	***0.25***	***0.5***

Table 8: Cluster Matrix

	accuracy	*Complexity*	*Importance*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*
Accuracy	0.00	0.13	0.38	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
Complexity	0.19	0.00	0.38	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Important	0.56	0.63	0.00	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38
1	0.05	0.03	0.06	0.00	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.07	0.06
2	0.00	0.03	0.01	0.06	0.00	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.06
3	0.01	0.02	0.01	0.02	0.05	0.00	0.05	0.05	0.05	0.05	0.05	0.05	0.02	0.02
4	0.01	0.02	0.01	0.07	0.05	0.05	0.00	0.05	0.05	0.05	0.05	0.05	0.06	0.06
5	0.01	0.02	0.01	0.04	0.05	0.05	0.05	0.00	0.05	0.05	0.05	0.05	0.04	0.04
6	0.01	0.01	0.01	0.05	0.05	0.05	0.05	0.05	0.00	0.05	0.05	0.05	0.05	0.05
7	0.01	0.03	0.01	0.04	0.05	0.05	0.05	0.05	0.05	0.00	0.05	0.05	0.05	0.04
8	0.02	0.04	0.01	0.10	0.05	0.05	0.05	0.05	0.05	0.05	0.00	0.05	0.10	0.08
9	0.01	0.02	0.01	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.00	0.04	0.04
10	0.05	0.02	0.03	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.00	0.06
11	0.07	0.02	0.07	0.02	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.02	0.00

Table 9: Harmonious super-matrix

3.3.5. Extracting Priorities from a Super-matrix

After forming a limited super-matrix, the elements of the clusters of alternatives and criteria got a fixed and corresponding weight. These weights were the final weights of these elements for decision making. The final priorities and obtained weights from Super

	accuracy	Complexity	Importance	1	2	3	4	5	6	7	8	9	10	1
accuracy	0.173	0.173	0.173	0.173	0.173	0.173	0.173	0.173	0.173	0.173	0.173	0.173	0.173	0.173
Complexity	0.167	0.167	0.167	0.167	0.167	0.167	0.167	0.167	0.167	0.167	0.167	0.167	0.167	0.167
Importance	0.327	0.327	0.327	0.327	0.327	0.327	0.327	0.327	0.327	0.327	0.327	0.327	0.327	0.327
1	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
2	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024
3	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021
4	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023
5	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020
6	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024
7	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025
8	0.034	0.034	0.034	0.034	0.034	0.034	0.034	0.034	0.034	0.034	0.034	0.034	0.034	0.034
9	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024	0.024
10	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039	0.039
11	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050

Table 10: Limited Super-matrix

Decisions Software are as presented in Table 11.

Limiting	Normalized By Cluster	Name
0.173098	*0.25965*	**Difficulty**
0.166748	*0.25012*	**Complexity**
0.326821	*0.49023*	**Importance**
0.049752	*0.14926*	**1**
0.023691	*0.07107*	**2**
0.020708	*0.06212*	**3**
0.022844	*0.06853*	**4**
0.020094	*0.06028*	**5**
0.024259	*0.07278*	**6**
0.025082	*0.07525*	**7**
0.033737	*0.10121*	**8**
0.023627	*0.07088*	**9**
0.039106	*0.11732*	**10**
0.050433	*0.1513*	**11**

Table 11: The final weights obtained from the super-matrix

3.4. Converting the Obtained Weights to Questions' Scores

One of the characteristics of the proposed algorithm is its goal to adjust the initial scores presented by question designers, just the opposite of previous algorithms. This algorithm presents the initial question scores itself by taking into account the expert view and the

Question Number(i)	Normalized Weight (Wi)	Final Score(Gi)
1	*0.14926*	*2.9852*
2	*0.07107*	*1.4214*
3	*0.06212*	*1.2424*
4	*0.06853*	*1.3706*
5	*0.06028*	*1.2056*
6	*0.07278*	*1.4556*
7	*0.07525*	*1.505*
8	*0.10121*	*2.0242*
9	*0.07088*	*1.4176*
10	*0.11732*	*2.3464*
11	*0.1513*	*3.026*

Table 12: Converting weights to the final scores of questions

results of the extracted questions. In this step, final calculations for determining the questions' score weights were conducted. Relation 8 was used for this purpose in which the amount of parameter S was 20. The final results can be observed in Table 12.

4. Conclusion

Evaluating educational development is a highly important and applicable process in any educational system. In this process, the trend of changing qualitative variables to quantitative ones has always attracted teachers' attention; however, its precision has been skeptical since many years ago. In this paper, a combined method is presented for determining the weight of scientific exam scores. In this model, a part of PROMETHEE method, called preference function, formed the inputs of one of the pairwise comparison matrices, which was used in the fuzzy analytic network process. In data preparation step, data mining approach was used before PROMETHEE. Compared with the previously conducted researches, this method has the following advantages: first, the proposed method is the method of constructing the initial score weights while previous methods only tried to adjust initial score weights presented by teachers using similar criteria. Considering that the goal of the conducted studies was to remove human evaluation errors, using the initial score weights as the main basis does not make sense. Second, the analytic network process gives acceptable results in spite of all the current dependency in the network. In addition, preference function provides an opportunity to use the real information extracted from the answer sheets; these data are real; so they are more reliable. Moreover, data mining approach leads to the reduction in the influence of noisy and incomplete data in the conducted studies and, as a result, improves the performance and precision of the method in the exams with a large number of test-takers and questions. Investigating previous works in the field of evaluating educational development and also the combined methods of decision making using the multi-criteria show that the proposed method is unique due to integrating four different fields of data mining, analytic network process, fuzzy collection and preference function.

5. Future Research

The proposed method has been used and verified in a case study conducted at Qazvin Islamic Azad University. For future studies, the proposed method can be applied in other decision making problems that requires to allocate weights to alternatives and ranking them. For instance:

- various fields of supply chain management, especially in discount models.
- In project management for selecting an appropriate portfolio, especially R&D projects.

On the other hands evaluating the impact of these for improvement of model can be considered :

- Using other types of preference function
- Using other data mining tools
- Using other types of fuzzy numbers

Appendix 1: Initial results of data gathering

SUM	FINAL	11	10	9	8	7	6	5	4	3	2	1	Student Number
12.3	12.3	2.9	2.2	1	0.9	0.8	1	0.8	0.6	0	0.3	1.8	**61**
11.1	11.1	2.7	2.4	0.2	0.3	0.8	1	0.8	0.8	0.4	0.3	1.4	**62**
12.4	12.4	3.2	2.8	0	0	0.6	1	0.5	0.9	0.8	0.8	1.8	**63**
12.8	12.4	2.5	3.2	0.7	0.6	0.8	0.8	0.4	0.7	0.8	0.7	1.6	**64**
10.6	10.6	2.9	2.4	0.7	1.1	0.8	1	0.6	0.2	0.7	0.2	0	**65**
11.8	11.8	2.7	1.5	0.2	0.7	0.8	0.7	0.6	0.8	1	1	1.8	**66**
10.9	10.9	2.4	0.8	0.9	0	0	1	0.6	0.8	0.6	1.2	2.6	**67**
13.1	13.1	3.3	2.2	1	1.2	0.9	1	0	1	0.8	0	1.7	**68**
16.8	16.8	3.3	2.8	1	1.3	1	1	1	0.9	0.8	1.5	2.2	**69**
12.7	12.7	3.4	2.7	0.2	1	0.7	1	0.6	0.2	0.4	1.1	1.4	**70**
13.2	13.2	3.2	2.8	0.6	0	1	0.9	0.7	1	0.9	0.8	1.3	**71**
13	13	3.4	1.8	1	0.7	0.8	0.7	0.8	0.8	0.8	0.6	1.6	**72**
SUM	**FINAL**	**11**	**10**	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**	**Student Number**
11.1	11.1	2.4	2	0.8	0.1	0.9	0.4	0.8	1	0.8	0.6	1.3	**73**
13.8	13.8	3	2.3	0.8	0.2	1	1	0.8	1	0.8	1.2	1.7	**74**
14.4	14.4	3.3	1.8	1	1.3	0.9	0.8	1	0.6	0.7	0.8	2.2	**75**
8.1	8.1	0	2.7	0.2	0.3	0.3	0.8	0.9	0.5	0.8	0.9	0.7	**76**
10.5	10.5	2	2.1	0.2	1.2	0.8	0.7	0.4	1	0.7	0.2	1.2	**77**
11.1	11.1	2.3	2.6	0	0	0.7	0.8	0.6	1	0.5	0.3	2.3	**78**
9.3	9.3	3.2	2.4	0.5	0	0	0	0.7	1	0.8	0.7	0	**79**
12.2	12.2	2.9	2.1	0.8	0	0.9	0.9	0.6	1	1	0.2	1.8	**81**
13.3	13.3	2.8	2.2	0.8	1	0.8	1	0.5	0.7	0.8	1	1.7	**82**
13.1	13.1	3.2	1.8	0.8	1.3	0.9	1	0.8	0.7	0.6	0.6	1.4	**83**
14.4	14.4	3.4	2.2	1	0.5	1	1	0.7	1	0.7	1.3	1.6	**86**
11.6	11.6	2.7	2.6	0.3	1	0.3	0.8	0.7	1	0.4	0.3	1.5	**87**
9.3	9.3	0	2.1	1	0.4		0.7	0.7	1	0.8	1.2	1.4	**88**
10	10.1	2.8	1.8	0.3	0.7	0.5	0.3	0.7	1	1	0.4	0.5	**89**
10.5	10.5	1.7	2.3	0.9	0.8	0.8	0.9	0	1	0.8	0.3	1	**90**
10.9	10.9	1	2.7	1	1	0.8	1	0.7	0.2	0.9	0.3	1.3	**91**
14.8	14.8	3	2.9	1	1.3	1	0.8	0.8	1	0.8	0.5	1.7	**92**
13.1	13.1	2.6	2.4	0.5	1.3	0.9	0.7	0.8	1	0.9	0.5	1.5	**93**
16	15.5	3.3	2.8	1	1.2	1	1	0.8	1	0.8	1.2	1.9	**95**
15.5	16.5	3.2	2.6	1	1.5	1	0.8	0.9	1	1	0.7	1.8	**96**
8.5	8.5	1.8	2.3	0.8	0.5	0.5	0.6	0	0	0.4	0.3	1.3	**97**
10.3	10.3	2	1.7	0.7	0	0	0.6	0.7	0.5	1	1.3	1.8	**98**
11.2	11.2	2.2	1.8	0.7	0.7	1	0.8	0	0.8	1	0.8	1.4	**99**
12.3	12.3	2.2	2.3	0.2	0.5	0.7	0.9	0.7	1	0.8	0.7	2.3	**100**
11.9	11.9	1.3	2.9	0.9	0.8	0.8	1	0.6	0.6	1	0.4	1.6	**101**
15.9	15.9	2.8	2.9	1	1.5	1	1	0.8	1	1	1.4	1.5	**102**
15.4	15.4	2.1	2.7	1	1.5	1	1	1	1	1	0.5	2.6	**103**
12.8	12.8	2.3	2.8	0.8	1.1	0.8	0.8	0.5	0.8	0.6	0.3	2	**104**

9.9	9.9	2.6	1.4	0.6	0.6	0.3	0.8	0.7	0.7	0.9	0.3	1	**105**
11.4	11.4	1.8	2.3	0.8	0.9	0.8	1	1	0	0.7	0.4	1.7	**106**
15	15	2.8	2.7	1	1.2	0.7	0.8	1	0.9	0.9	0.7	2.3	**107**
14.3	14.3	3	2.9	1	1.3	0.8	1	0.2	0.8	0.9	0.6	1.8	**108**
14.3	14.3	3.1	3.2	1	0.9	0.7	0.8	0.8	0.7	0.1	1.2	1.8	**109**
14.5	14.5	2.3	3.1	1	1.3	0.4	1	0.8	1	0.4	0.9	2.3	**110**
14.5	14.5	3	2.6	1	0.2	0.9	1	1	1	1	1.1	1.7	**111**
9.3	9.3	2.3	2.2	0	0.6	0	0.6	0.6	0.8	0.2	0.6	1.4	**112**
13.8	13.8	2.8	2.8	0.8	1.4	0.9	1	0.8	0.8	0.8	0.4	1.3	**113**
14.7	14.7	2.8	2.9	0.8	0.9	0.8	0.8	0.7	1	0.6	1	2.4	**114**
13.2	13.2	2.6	2.8	0.6	0	0.7	0.9	0.9	0.9	0.7	0.8	2.3	**115**
12.8	12.8	2.8	1.7	0.4	1.3	0	0.7	0.6	1	1	0.7	2.6	**116**
13	13	2.4	2.3	0.6	1.4	0	0.8	0.8	1	0.9	0.4	2.4	**117**
15.4	15.4	2.8	2.8	1	1.3	0.9	1	0.6	0.3	1	1.5	2.2	**118**
14.5	14.5	2	2.7	1	1.5	0.8	1	0.8	1	0.7	1.3	1.7	**119**
12.1	12.1	2.8	2.4	0.3	0.9	0.8	0.7	0.5	0.5	0.6	0.4	2.2	**120**
7.7	7.7	2.4	1	0.2	0	0	0.7	0.8	0	1	0.3	1.3	**161**
11.9	11.9	2.7	1.8	0.3	0.7	0.8	0.7	0.6	0.8	1	0.5	2	**162**
8.2	8.2	2.8	1.3	1	0.6	0.7	1	0	0.8	0	0	0	**164**
10.2	10.2	2.8	2.1	0	0.4	0	0.9	0.8	1	0.6	0.2	1.4	**166**
7.3	7.3	0	2.3	0.6	0	0.5	0.5	0.7	1	0.7	0.7	0.3	**167**
13	13	2.9	2.7	0.6	0.5	0.7	0.7	0.6	0.7	1	1	1.6	**168**
15.8	15.8	3	2.6	1	0.9	0.9	1	1	1	0.6	1.5	2.3	**169**
9.7	9.7	3	2.4	0	0.3	0	0.5	0.4	0.2	1	0.3	1.6	**170**
11.9	11.9	2.7	2.3	0.2	1.1	0.3	1	1	0.2	1	0.5	1.6	**171**
12.1	12.1	2.3	1.8	0.8	0.6	1	0.9	0.8	1	0.8	0.4	1.7	**172**
11.1	11.1	2.2	2.2	1	0.4	0.5	1	0	0.8	1	0.4	1.6	**173**
9.7	9.7	2.4	1.7	0.3	0	0	1	0.6	1	0	1.3	1.4	**174**
11.6	11.6	2.4	1.8	0	0.8	1	0.8	1	0.2	0.7	1	1.9	**175**
10.5	10.5	2	2.4	0.4	0.5	0.5	0.7	0.7	0	0.3	0.8	2.2	**176**
8.4	8.4	2.7	1.4	0.8	0	0	0.6	0	0	1	0.4	1.5	**177**
12.6	12.6	3.2	1.9	1		0.4	1	1	0.4	1	1	1.7	**178**
13.1	13.1	2.5	2.3	1	1.4	1	0.9	0.4	0	1	0.3	2.3	**179**
15	15	2.8	3.1	1	1.2	0.9	1	0.7	0.8	1	1	1.5	**180**
9.6	9.6	2.4	2.1	0.4	0	0.3	0.5	0.6	0	0.6	0.3	2.4	**181**
13.2	13.2	2.8	2.7	1	1.2	0.7	0.8	0.4	1	0.6	0.2	1.8	**182**
10.3	10.3	2.7	1.2	0.7	0.7	0.5	0.4	0.6	1	0.8	0.4	1.3	**183**
8.8	8	2.2	2.4	0	0	0.4	0.4	0	0.9	0.4	0.5	1.6	**184**
14.8	14.8	2.7	2.6	1	0	1	1	0.8	1	1	1.5	2.2	**185**
12.5	12.5	3.2	2.6	1	1.1	1	0.8	0	0.8	0.8	0	1.2	**187**
12.6	12.6	2.4	2.7	0.6	1	0.8	0.9	0.7	0.8	1	0.4	1.3	**188**
11.2	11.2	2.2	1.4	0	1.2	1	0.9	0.6	0.9	0.8	0.4	1.8	**189**
6.4	6.4	0.3	2.6	0.3	0.3	0	0.2	0.5	0.3	0	0.3	1.6	**191**
9.9	9.9	2.5	2.3	0	0	0	0.4	0.8	1	0.7	0.8	1.4	**192**
9.6	9.5	2.4	2.1	0.2	0.3	0	0.7	0.8	0	1	0.6	1.5	**193**
8.8	8.8	3.3	3.7	0	0	0	0	0.8	1	0	0	0	**194**
14.3	14.3	3.2	2.6	0.9	1	0.8	0.9	0.6	1	0.7	0.8	1.8	**195**
SUM	**FINAL**	**11**	**10**	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**	**Student Number**
13.7	13.7	2.8	2.4	0.9	1.1	1	0.8	0.7	0.8	1	0.5	1.7	**196**
13.1	13.1	3.2	2.6	0.7	1.2	0.9	1	0.8	0.2	0.7	0.4	1.4	**197**
7	7	3	2.8	1	0	0	0	0	0	0	0.2	0	**M1**
12.9	12.9	3.2	2.3	0.6	0.2	0.6	0.6	0.7	1	0.6	0.5	2.6	**M2**

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