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The 2-Tuple Linguistic Representation Approach for Learning Competence Evaluation

Sri Andayani
Department of Mathematics Education
Yogyakarta State University
Indonesia
andayani_uny@yahoo.com

Abstract

In this paper, we will consider the use of 2-tuple linguistic representation model in the evaluation of learning competence. The 2-tuple linguistic representation model has been widely used in various applications and enhance the results of the decision-making process which involves the qualitative aspects. As is known, learning assessment can be viewed as a form of decision-making to evaluate the learning competence achieved by students, and usually the result of the decision are presented in figures. In the process, preferences of teachers as decision makers on student competence involves quantitative and qualitative aspects. Quantitative aspects can be easily represented with numeric, while the qualitative aspect more precisely represented by using linguistic variables.

The use of linguistic variables to represent qualitative aspects are considered very appropriate to be applied in evaluating student competency. The 2-tuple linguistic representation as an advanced model of ordinary linguistic variables strongly support the utilization. Therefore, in this paper we proposed stages of implementation of 2-tuple linguistic representation to evaluate the competence of student learning outcomes.

The stages are as follows: (1).Transform the linguistic information in the decision matrix $\mathrm{R} = (\mathrm{r}_{ij})_{m\times n}$ be a 2-tuple linguistic $\overline{\mathrm{R}} = (\bar{\mathrm{r}}_{ij})_{m\times n}$; (2). Calculating the degree of importance of evaluation competency; and (3). Aggregating the information from the previous stages using 2-tuple linguistic operators to obtain the final results.
Keywords: 2-tuple linguistic, learning assessment, decision making.

1. Introduction

Decision making is an issue involving a limited set of alternatives $X = \{x_1, x_2, \dots, x_n\}, n \geq 2\}$, and the best alternative of X is determined on the basis of assessment information by decision makers D on a set of criteria $C = \{c_1, c_2, \dots, c_p\}, p \geq 2\}$. Assessment of learning outcomes is a form of decision-making, to evaluate the competence of learning outcomes achieved by students and usually the final result are presented in figures. In models of decision making, is a collection of alternative X students who will be ranked in order to obtain the sequence of the best to the worst alternatives. Competency acts as a set of criteria C in the granting of preferences by teachers, and the importance weights need to be determined.

Preferences of student competence given by the teacher as a decision maker involves quantitative and qualitative aspects. Quantitative aspects can be easily represented with numerical data, while the qualitative aspect more precisely represented by using linguistic variables. Linguistic variable is a variable whose value is not numbers but words or sentences in natural language and the words are characterized by fuzzy sets defined in the universe defined set [12].

The computational techniques for dealing with linguistic terms can be classified into three categories [3], i.e. the extension principle, the symbolic method, and the 2-tuple fuzzy linguistic representation model. In the former two approaches, the results usually do not exactly match any of the initial linguistic terms, then an approximation process must be developed to express the result in the initial expression domain. This produces the consequent loss of information and hence the lack of precision. Whereas, the third kind of approach overcomes the above limitations. Therefore, the approach based on the 2-tuple fuzzy linguistic representation model is more convenient and precise to deal with linguistic terms in solving MCDM problems

The aim of this paper is to extend the concept of solving MCDM problems under linguistic environment, to solve the learning competence evaluation problems. The extension includes the information about criteria weights and the criteria values in form of linguistic variables. In order to do this, the remaining of this paper is organized as follows: In Section 2, we briefly reviews basic definitions of the 2-tuple fuzzy linguistic approach and some aggregation operators. The proposed method to solve learning competence evaluation problems based on 2-tuple linguistic approach is presented in Section 3. Section 4 presents an illustrative example of competence evaluation assessments problem. The paper is concluded in Section 5.

2. The 2-Tuple Fuzzy Linguistic Representation

Fuzzy linguistic approach has been successfully applied in many problems. However, there are limitations of computing with fuzzy linguistic approach, namely the loss of information due to the need to express the results in the discrete initial domain through the estimation process. Herrera and Martínez [2], [3] initiated studies using fuzzy approach to 2-tuple linguistic translation to overcome these limitations. This approach in the development of many implemented in a variety of applications, including for the evaluation of computer network security systems [14], the evaluation of employee competencies [2], a method for evaluating the risk of high-level technology [7], evaluate emergency response capacity [6], tourist management [13], and the prevention and reduction capacity assessment floods [8].

The fuzzy linguistic approach represents qualitative aspects as linguistics values by means of linguistic variables. The linguistic descriptors for the linguistic term set and its semantics must be appropriately determined. To do so, an important aspect need to be analyzed, i.e. the granularity of uncertainty, that is the level of discrimination among diferent counts of uncertainty. The odd cardinality is usually used as typical value in the linguistic models, such as 7 or 9, where the mid term shows an assessments of “approximately 0.5” and the rest of the term being places symmetrically around it.

The linguistic term set and its semantics can be generated by directly assigning the term set of which all the terms will be distributed on a scale where a total order is defined [3]. For example, let $S = \{s_i \mid i = 0, \ldots, g\}$ be a linguistic term set with odd cardinality. A seven term set of S is given as follows:

S ={s_0= *extremely poor (EP);* s_1= *very poor (VP);* s_2= *poor (P);* s_3 =*medium (M);*
s_4 =*good (G);* s_5= *very good (VG);* s_6= *extremely good (EG)*}

Any label, s_i represents a possible value for a linguistic variable, and there exist:

1). A Negation operator: $Neg(s_i) = s_j$ such that $j = g - i$ ($g + 1$ is the cardinality).

2). $s_i \leq s_j \Leftrightarrow i \leq j$. Therefore there exists a minimization and a maximization operator, that are: $\max(s_i, s_j) = s_i, if\ s_i \geq s_j$; $\min(s_i, s_j) = s_i, if\ s_i \leq s_j$

The semantics of the terms is given by fuzzy number defined in [0,1] interval, which are usually described by membership functions. The linear trapezoidal membership function are good enough to represents the linguistic value due to vagueness of assessment given by the users. This is denoted by the 4-tuple $\bar{A} = (a, b, c, d)$ and the membership function of $\bar{A}$ is as follows.

$$\mu_{\bar{A}}(x) = \begin{cases} 0 & x < a_1, \\ \frac{x-a_1}{a_2-a_1} & a_1 \leqslant x \leqslant a_2, \\ 1 & a_2 \leqslant x \leqslant a_3, \\ \frac{x-a_4}{a_3-a_4} & a_3 \leqslant x \leqslant a_4, \\ 0 & x > a_4. \end{cases}$$

For example, the set of seven terms S can be assigned by the semantics as in Table 1 and is graphically shown in Fig. 1.

Table 1. Linguistic terms and its semantics

Linguistic variable	Trapezoidal fuzzy number
Extremely poor (EP)	(0.0, 0.0, 0.1, 0.2)
Very poor (VP)	(0.0, 0.0, 0.2, 0.3)
Poor (P)	(0.0, 0.0, 0.4, 0.5)
Medium (M)	(0.4, 0.5, 0.5, 0.6)
Good (G)	(0.5, 0.6, 1, 1)
Very good (VG)	(0.7, 0.8, 1, 1)
Extremely good (EG)	(0.8, 0.9, 1, 1)

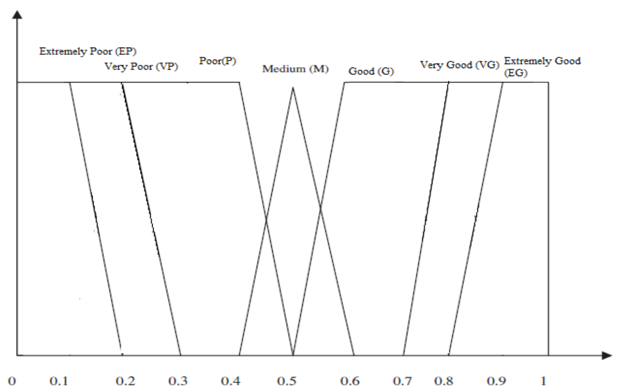

Figure 1. Linguistic terms set of seven labels and its semantics

Herrera and Martinez [3],[4],[5] proposed a model of linguistic information expressed through 2-tuple (s, α), which is compiled by the linguistic term s and α assessed numerical values in the interval [-0.5, 0.5]. This model allows a continuous representation of linguistic information in its domain, therefore, may represent a tally of information obtained in the process of aggregation.

The 2-tuple fuzzy linguistic models take the basic model of symbolic and symbolic translation concepts and then use it to represent the linguistic information through a pair of values, called linguistic 2-tuple, (s,α). S notation is used to represent

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linguistic terms, while α is used to present a numerical value representing the symbolic translation.

Definition 1. The symbolic translation of a linguistic term $s_i \in S = \{s_0, \ldots, s_g\}$ consists of a numerical value $\alpha_i \in [-0.5, 0.5)$ that supports the "difference of information" between a counting of information β assessed in $[0, g]$ obtained after a symbolic aggregation operation (acting on the order index of the labels) and the closest value in $\{0, \ldots, g\}$ that indicates the index of the closest linguistic term in $S(s_i)$.

The linguistic representation model defines a set of functions to make transformations between linguistic terms, 2-tuples and numerical values [2].

Definition 2. Let $s_i \in S$ be linguistic term, then its equivalent 2-tuple representation is obtained by means of the function θ as:

$$\theta: S \to (S \times [-0.5, 0.5))$$
$$\theta(s_i) = (s_i, 0), \quad s_i \in S \qquad (1)$$

A crips value $\beta \in [0, g]$ can be transformed into the 2-tuple linguistic variable using the following definition.

Definition 3. Let $S = \{s_0, \ldots, s_g\}$ be a linguistic term set, $\beta \in [0, g]$ is a number value representing the symbolic aggregation result of linguistic term. Then the 2-tuple that expresses the equivalent information to β is obtained using the following function:

$$\Delta: [0, g] \to S \times [-0.5, 0.5]$$
$$\Delta(\beta) = (s_i, \alpha)$$
$$\text{where } \begin{cases} s_i, & i = round(\beta) \\ \alpha = \beta - i & \alpha \in [-0.5, 0.5) \end{cases} \qquad (2)$$

where round is the usual rounding operation, s_i has the closest index label to β and α is the value of the symbolic translation.

Definition 4. Let $S = \{s_0, \ldots, s_g\}$ be a linguistic term set and (s_i, α) is 2-tuple linguistic information, then there exists a function Δ^{-1} which is able to transform 2-tuple linguistic information into its equivalent numerical value $\beta \in [0, g] \subset R$:

$$\Delta^{-1}: S \times [-0.5, 0.5] \to [0, g]$$
$$\Delta^{-1}(s_i, \alpha) = i + \alpha = \beta \qquad (3)$$

3. Learning Competency Evaluation using The 2-Tuple Linguistic

Some aggregation operators for 2-tuple linguistic variables defined in Moreno et al [9]. Among them is the arithmetic mean, weighted average, and linguistic weighted average operator. On the basis of these operators, this paper will describe the stages are carried out in a 2-tuple linguistic use for the evaluation of competence of student learning outcomes. The stages are as follows:

(1).Transform the linguistic information in the decision matrix $R = (r_{ij})_{m\times n}$ be a 2-tuple linguistic $\bar{R} = (\bar{r}_{ij})_{m\times n}$;

(2). Calculating the degree of importance of evaluation competency using Fuzzy Analytic Network Process; and

(3). Aggregating the information from the previous stages using 2-tuple linguistic operators to obtain the final results.

Results are expected by the use of 2-tuple linguistic competence to evaluate student learning outcomes is contributing to support the resolution of problems in the process of assessment. Particularly in relation to their coverage of quantitative and qualitative aspects, so it can produce a more valid assessment, fair and reliable.

a. Transforming the linguistic information into 2-tuple Fuzzy Linguistic

Preference given by the teacher to the student consists of linguistic information is presented in the form of a decision matrix. Furthermore, each element in the matrix is transformed into 2-tuple linguistic representation, using equation (1). If there is more than one decision matrix, it is required steps to aggregate into a final matrix that is ready to be operated using 2-tuple linguistic operators. This step involves the equations (2) and (3).

b. Calculating the degree of importance of evaluation competency using Fuzzy Analytic Network Process;

Importance level (weight) of competence is determined by means of the Fuzzy Analytic Network Process (FANP) method. The steps are as follows [1].

1. Develop an ANP framework
   The ANP framework is a network which is composed of relationships between of a goal, a set of factors and related criteria.
2. Determine Local weights
   The local weights of the factors and criteria are determined by pair-wise comparisons using linguistic variables. The factors are compared with each other assuming that there is no interdependency among them. To calculate the local weights, the values of fuzzy numbers should be calculated first using fuzzy AHP approach proposed by Chang, and known as Chang's extent analysis [10]. In these methods, the analysis of each criterion, g_i, performed in order to obtain *m* values for each criterion as follows.

$$M_{g_i}^1, M_{g_i}^2, M_{g_i}^3, M_{g_i}^4, \ldots, M_{g_i}^m$$

where $g_i, (i = 1,2,3,4,5, \ldots, n)$ is set of goals and $M_{g_i}^j$ $(j = 1,2,3,4,5, \ldots, m)$ are triangular fuzzy numbers (TFN).

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The steps of Chang's extent analysis can be given as follows:

(Step 1) The value of fuzzy synthetic extent with respect to the i^{th} object is defined as

$$S_i = \sum_{j=1}^{m} M_{g_i}^{j} \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j} \right]^{-1}$$

where

$$\sum_{j=1}^{m} M_{g_i}^{j} = \left(\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j \right)$$

and

$$\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j} = \left(\sum_{i=1}^{n} l_i, \sum_{i=1}^{n} m_i, \sum_{i=1}^{n} u_i \right)$$

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j} \right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i} \right)$$

(Step 2) The degree of possibility of $M_2 = (l_2, m_2, u_2) \geq M_1 = (l_1, m_1, u_1)$ is defined as

$$V(M_2 \geq M_1) = \sup_{y \geq x} \left[\min \left(\mu_{M_1}(x), \mu_{M_2}(y) \right) \right]$$

and can be expressed equivalently as follows

$$V(M_2 \geq M_1) = hgt(M_1 \cap M_2) = \mu_{M_2}(d)$$

$$= \begin{cases} 1, & if\ m_2 \geq m_1 \\ 0, & if\ l_1 \geq u_2 \\ \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)} & others \end{cases}$$

d is the ordinate of the highest intersection (hgt) between μ_{M_1} and μ_{M_2}. To compare M_1 and M_2 we need the values of $V(M_1 \geq M_2)$ and $V(M_2 \geq M_1)$

(Step 3) The degree possibility for a convex fuzzy number to be greater than k convex fuzzy numbers M_i $(i = 1,2,3,4,5, \dots, k)$ can be defined by

$$V(M \geq M_1, M_2, \dots, M_k) = V[(M \geq M_1)\ and\ (M \geq M_2)\ and \dots and\ (M \geq M_k)]$$

$$= \min\ V(M \geq M_i), i = 1,2,3, \dots, k$$

Assume that $d'(A_i) = \min V(S_i \geq S_k)$

For $k = 1,2,3,4,5, \dots, n, k \neq i$.

Then, the weight vector is given by

$$W' = (d'(A_1), d'(A_2), \dots, d'(A_n))^T$$

(Step 4). Via normalization, the normalized weight vectors are

$$W = (d(A_1), d(A_2), \dots, d(A_n))^T$$

3. Determine Interdependent weights
   Interdependent weights is determined by multiplying the dependence matrix with the local weights of main factors which is calculated in previous step. The dependence matrix consists of the inner dependence of each factor which is constructed regarding the other factors with fuzzy scale.
4. Determine Global weights
   The global weights of the criteria are calculated using interdependent weights of the factors and each of local weight of the criteria.

c. Aggregating the information using 2-tuple linguistic operators

In this step, arithmetic mean and weighted average operator will be utilized to aggregate the 2-tuple linguistic information in order to obtain the final result. The operators are defined as follows.

Definition 5. Let $\boldsymbol{x} = \{(\boldsymbol{s_1}, \boldsymbol{\alpha_1}), (\boldsymbol{s_2}, \boldsymbol{\alpha_2}), \dots, (\boldsymbol{s_n}, \boldsymbol{\alpha_n})\}$ be a 2-tupel linguistic set, then the arithmetic mean is

$$(\bar{s}, \bar{\alpha}) = \Delta\left(\frac{1}{n}\sum_{j=1}^{n} \Delta^{-1}(s_j, \alpha_j)\right), \bar{s} \in S, \bar{\alpha} \in [-0.5, 0.5) \quad (4)$$

Definition 6. Let $\boldsymbol{x} = \{(\boldsymbol{s_1}, \boldsymbol{\alpha_1}), (\boldsymbol{s_2}, \boldsymbol{\alpha_2}), \dots, (\boldsymbol{s_n}, \boldsymbol{\alpha_n})\}$ be a 2-tuple linguistic set, and $\omega = (\omega_1, \omega_2, \dots, \omega_n)$ be the weighting vector of 2-tuples (s_j, α_j) $(j = 1, 2, \dots, n)$ and $\omega_1 \in [0,1], j = 1,2, \dots, n, \sum_{j=1}^{n} \omega_j = 1$ then the two-tuple weighted average is

$$(\bar{s}, \bar{\alpha}) = \varphi((s_1, \alpha_1), (s_2, \alpha_2), \dots, (s_n, \alpha_n))$$

$$= \Delta\left(\frac{1}{n}\sum_{j=1}^{n} \omega_j \Delta^{-1}(s_j, \alpha_j)\right), \bar{s} \in S, \bar{\alpha} \in [-0.5, 0.5) \quad (5)$$

4. Illustrative Example

Suppose a teacher will assess the learning competence of students, which is determined by the 4 competencies (as a parameter) which will be assessed by means of three kinds of evaluation methods, i.e. observation, assignments and portfolios.

For example, there are six students to be assessed, $A_i, i = 1, \dots, 6$. The decision matrix could be used to represent the assessment value is

$$R_k = \left(r_{ij}^{(k)}\right)_{6x4} (k = 1,2,3)$$

where $r_{ij} = (s_{ij}, \alpha_{ij}),\ s_{ij} \in S,\ i = 1,..,6; j = 1,..,4$

The linguistic term set S used in the assessment is:

S ={s_0= extremely poor (EP); s_1= very poor (VP); s_2= poor (P); s_3 =medium (M); s_4 =good (G); s_5= very good (VG); s_6= extremely good (EG)}

For example, performance value given by the teacher construct the decision matrix as below.

R_1 =

	C_1	C_2	C_3	C_4
A_1	P	VP	M	P
A_2	VG	P	P	G
A_3	M	G	P	P
A_4	G	M	G	EP
A_5	EG	EP	VP	M
A_6	P	M	VP	VP

R_2 =

	C_1	C_2	C_3	C_4
A_1	G	VG	EG	VP
A_2	VG	VP	G	P
A_3	M	VP	M	G
A_4	VP	G	P	G
A_5	G	P	VP	VG
A_6	G	M	G	EP

R_3 =

	C_1	C_2	C_3	C_4
A_1	P	M	VP	VP
A_2	EG	VP	VP	M
A_3	M	G	P	EG
A_4	VP	EP	G	G
A_5	P	VP	M	VP
A_6	G	M	G	EP

The next step is transform the decision matrix $R = (r_{ij})_{m\times n}$ to be 2-tuple linguistic matrix $\bar{R} = (\bar{r}_{ij})_{m\times n}$ using the equation (1).

R_1 =

	C_1	C_2	C_3	C_4
A_1	(P,0)	(VP,0)	(M,0)	(P,0)
A_2	(VG,0)	(P,0)	(P,0)	(G,0)
A_3	(M,0)	(G,0)	(P,0)	(P,0)
A_4	(G,0)	(M,0)	(G,0)	(EP,0)
A_5	(EG,0)	(EP,0)	(VP,0)	(M,0)
A_6	(P,0)	(M,0)	(VP,0)	(VP,0)

R_2 =

	C_1	C_2	C_3	C_4
A_1	(G,0)	(VG,0)	(EG,0)	(VP,0)
A_2	(VG,0)	(VP,0)	(G,0)	(P,0)
A_3	(M,0)	(VP,0)	(M,0)	(G,0)
A_4	(VP,0)	(G,0)	(P,0)	(G,0)
A_5	(G,0)	(P,0)	(VP,0)	(VG,0)
A_6	(G,0)	(M,0)	(G,0)	(EP,0)

R_3 =

	C_1	C_2	C_3	C_4
A_1	(P,0)	(M,0)	(VP,0)	(VP,0)
A_2	(EG,0)	(VP,0)	(VP,0)	(M,0)
A_3	(M,0)	(G,0)	(P,0)	(EG,0)
A_4	(VP,0)	(EP,0)	(G,0)	(G,0)
A_5	(P,0)	(VP,0)	(M,0)	(VP,0)
A_6	(G,0)	(M,0)	(G,0)	(EP,0)

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The final decision matrix is determined from the three matrix above by using the equation (4), and yields

$$R = \begin{pmatrix} (M,-0.33) & (M,0) & (M,0.33) & (VP,0.33) \\ (VG,0.33) & (VP,0.33) & (P,0.33) & (M,0) \\ (M,0) & (M,0) & (P,0.33) & (G,0) \\ (P,0) & (P,0.33) & (M,0.33) & (M,-0.33) \\ (G,0) & (VP,0) & (P,-0.33) & (M,0) \\ (M,0.33) & (M,0) & (M,0) & (EP,0.33) \end{pmatrix}$$

Suppose the weight of criteria obtained from the calculation using FANP methods is w={0,32; 0,19; 0,21; 0,28}. Then the final results of student's assessment determined using the equation (5)

So, the final score for student #1 is computed as below.

$$(\bar{s},\bar{\alpha})_1 = \Delta\left(\frac{0.32 \times 2.67 + 0.19 \times 3 + 0.21 \times 3.33 + 0.28 \times 1.33}{0.32 + 0.19 + 0.21 + 0.28}\right)$$

$$= \Delta(2{,}49)$$

$$= (P,\ 0.49) = (S_2,\ 0.49)$$

It means, the final assessment value of student #1 is P (*poor*). However, the value is tend toward M (medium), since there is $\alpha = 0.49$. Graphically, the value is shown in fig.2.

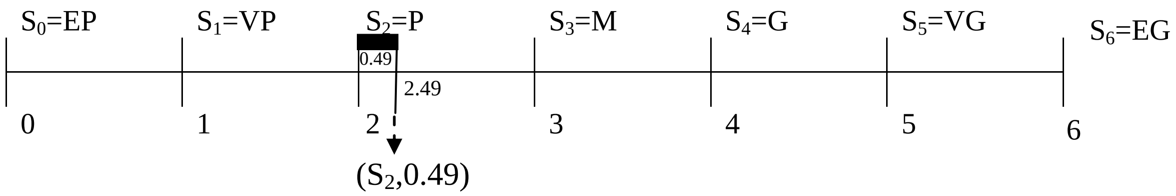

Figure 2. Representation of (S_2,0.49)

Further analysis is needed to define how important the sense of α on student learning outcomes. One thing that can be caught a glimpse of the value of α, is there a potential value that should be able to make students reach to the next level if α is positif and vice versa.

5. Conclusion

The modelling and handling of linguistic information for necessary computing are crucial in assessment of learning since there are qualitative aspects included in the assessment. Therefore in this paper we have proposed a method using 2-tuple linguistic representations to compute the assessment performance score that involve linguistic information. Though the method can avoid distortion and losing information which occur in the other linguistic information processing, it is still needed further analysis to define the importance meaning of α value to student learning outcomes.

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