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Some Average-Index Models of Intuitionistic Fuzzy Sets Applied to Practical Teaching Evaluation in University

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Abstract

Some average index models on intuitionistic fuzzy sets (IFS) are presented in this paper. By analyzing the membership function, the non-membership function and the hesitancy function, a weighted arithmetic mean index and a geometric mean index on IFS are introduced, along with the verification of some mathematical properties of these average Indexes. Finally, a multiple attribute decision making example applied to practical teaching evaluation is given to demonstrate the application of these statistical indexes. The simulation results show that the evaluation method of the average index is an effective method.

Keywords

Intuitionistic Fuzzy Sets; Practical Teaching Evaluation; Average Index

Introduction

In 1965, Professor L. A. Zadeh launched fuzzy sets (FS), which has influenced many researchers and has been applied to many application fields, such as pattern recognition, fuzzy reasoning, decision making, etc. In 1986, K. T. Atanassov introduced membership function, non-membership function and hesitancy function, and presented the concept of intuitionistic fuzzy sets (IFS), which generalized the FS theory. In the research field of IFS, Yager discussed its characteristics (2009), and more scholars applied it to decision making (Chen & Tan, 1994; Hong & Choi, 2000; Xu & Xia, 2007-2010; Zhang et al., 2012). Though many scholars have studied IFS and applied it to decision making, few references related to the study of education evaluation based on IFS were proposed. In 2012, Chen et al. studied a model for physical education evaluation in university, Wang et al. presented an approach to evaluate the class teaching quality and the student's creativity, and Zhang et al. presented a dynamic fuzzy sets method to evaluate the practical teaching according to IFS. In this paper, a novel average index method of IFS is presented, and applied to practical teaching evaluation.

First of all, the definition of IFS and some average indicators of IFS are introduced. And then, two novel average indexes of IFS are presented, followed by the application of the conventional average indicators and the novel average indexes to practical teaching evaluation in university. The simulation results show that the method introduced in this paper is an effective method.

Conventional Average Indicators of IFS

Definition 1. An IFS A in universe X is given by the following formula (Atanassov, 1986):

$$A = \{< x, \mu_A(x), v_A(x) > | x \in X\}. \tag{1}$$

Where $\mu_A(x) : X \to [0, 1]$, $v_A(x) : X \to [0, 1]$ with the condition $0 \le \mu_A(x) + v_A(x) \le 1$ for each $x \in X$. The numbers $\mu_A(x) \in [0,1]$, $v_A(x) \in [0, 1]$ denote a degree of membership and a degree of non-membership of x to A, respectively. For each IFS in X, we call $\pi_A(x) = 1 - \mu_A(x) - v_A(x)$ a degree of hesitancy of x to A, $0 \le \pi_A(x) \le 1$ for each $x \in X$.

According to IFS (Atanassov, 1986), we define a weighted arithmetic mean on membership degree and a weighted arithmetic mean on non-membership degree, respectively:

$$I_M(A) = \sum_{x \in X} w_A(x)\mu_A(x), I_{NM}(A) = \sum_{x \in X} w_A(x)\nu_A(x). \tag{2}$$

Based on a dominant ranking function (Chen & Tan, 1994), a weighted arithemetic mean on dominant ranking function can be expressed as follows:

$$I_{CT}(A) = \sum_{x \in X} w_A(x)(\mu_A(x) - \nu_A(x)). \tag{3}$$

Derived from Hong and Choi (2000), the following weighted arithemetic mean can be achieved:

$$I_{HC}(A)=\sum_{x\in X} w_A(x)(\mu_A(x)+\nu_A(x)). \tag{4}$$

Where $\mu_A(x)$ and $\nu_A(x)$ are membership function and non-membership function, respectively.

Let $A=\{<x, \mu_A(x), \nu_A(x)>|x\in X\}$, Ω_A denote the set constructed by all the IFS that we discuss.

$$A^+=\{<x,\max_{A\in\Omega_A}(\mu_A(x)),\min_{A\in\Omega_A}(\nu_A(x))>|x\in X\},$$
$$A^-=\{<x,\min_{A\in\Omega_A}(\mu_A(x)),\max_{A\in\Omega_A}(\nu_A(x))>|x\in X\},$$
$$\mu_{A^+}(x)=\max_{A\in\Omega_A}(\mu_A(x)),\nu_{A^+}(x)=\min_{A\in\Omega_A}(\nu_A(x)),$$
$$\mu_{A^-}(x)=\min_{A\in\Omega_A}(\mu_A(x)),\nu_{A^-}(x)=\max_{A\in\Omega_A}(\nu_A(x)),$$
$$\pi_{A^+}(x)=1-\mu_{A^+}(x)-\nu_{A^+}(x),\pi_{A^-}(x)=1-\mu_{A^-}(x)-\nu_{A^-}(x).$$

Then for each $A\in\Omega_A$, Xu presented the following formula (5) (2007):

$$R_{Xu}(A)=\frac{m(A^+,A)}{m(A^+,A)+m(A^-,A)}. \tag{5}$$

Using four distance measures, Xu provided four models from formula (5).

Some Average Indexes of IFS

According to Xu's formula (5), we define a basic index for each variable $x\in X$.

Definition 2. Suppose that T and F are two types of extreme IFSs in X, where $T=\{<x,1,0>|x\in X\}$ means $\mu_T(x)=1$ and $\nu_T(x)=0$, and $F=\{<x,0,1>|x\in X\}$ means $\mu_F(x)=0$ and $\nu_F(x)=1$. $I_k(A(x))$ (k=2, 3) is noted to be an index of IFS A for each $x\in X$. And we define:

$$\begin{aligned}I_3(A(x))&=\frac{m(A(x),F(x))}{m(A(x),F(x))+m(A(x),T(x))}\\&=\sqrt[p]{|\mu_A(x)|^p+|\nu_A(x)-1|^p+|\pi_A(x)|^p}\div\\&(\sqrt[p]{|\mu_A(x)|^p+|\nu_A(x)-1|^p+|\pi_A(x)|^p}\\&+\sqrt[p]{|\mu_A(x)-1|^p+|\nu_A(x)|^p+|\pi_A(x)|^p}).\end{aligned} \tag{6}$$

$$\begin{aligned}I_2(A(x))&=\frac{m(A(x),F(x))}{m(A(x),F(x))+m(A(x),T(x))}\\&=\frac{\sqrt[p]{|\mu_A(x)|^p+|\nu_A(x)-1|^p}}{\sqrt[p]{|\mu_A(x)|^p+|\nu_A(x)-1|^p}+\sqrt[p]{|\mu_A(x)-1|^p+|\nu_A(x)|^p}}.\end{aligned} \tag{7}$$

Then we define the following weighted arithemetic mean index:

$$IAM_k(A)=\sum_{x\in X} w_A(x)I_k(A(x)),k=2,3. \tag{8}$$

And we also obtain the following geometric mean index:

$$IGM_k(A)=\prod_{x\in X}(I_k(A(x)))^{w_A(x)},k=2,3. \tag{9}$$

Where m ($A(x)$, $T(x)$) and m ($A(x)$, $F(x)$) are distance measures. And we have $\sum_{x\in X} w_A(x)=1, w_A(x)\geq 0.$ When p=1, formula (8) and (9) are based on Hamming distance. Let p=1, we have (10) and (11):

$$\begin{aligned}IAM_3(A)&=\sum_{x\in X} w_A(x)\frac{1-\nu_A(x)}{2-\mu_A(x)-\nu_A(x)},\\IAM_2(A)&=\sum_{x\in X} w_A(x)\frac{\mu_A(x)+1-\nu_A(x)}{2}.\end{aligned} \tag{10}$$

$$\begin{aligned}IGM_3(A)&=\prod_{x\in X}(\frac{1-\nu_A(x)}{2-\mu_A(x)-\nu_A(x)})^{w_A(x)},\\IGM_2(A)&=\prod_{x\in X}(\frac{\mu_A(x)+1-\nu_A(x)}{2})^{w_A(x)}.\end{aligned} \tag{11}$$

We have $0\leq IAM_k(A)\leq 1$ and $0\leq IGM_k(A)\leq 1$ for each k and for each A. F indicates that all the example data are the firm opposition party of event A, thus we have $\mu_F(x)=0$, $\nu_F(x)=1$, and $\pi_F(x)=0$. And then we get $IAM_k(F)=0$ and $IGM_k(F)=0$, which means that the index of F is zero and the result of F is the worst. Similarly, we have $IAM_k(T)=1$and $IGM_k(T)=1$, which means that the result of T is perfect.

Definition 3. A and B are two IFSs over X, $A\subseteq B$ iff $\mu_A(x)\leq\mu_B(x),\nu_A(x)\geq\nu_B(x),$ for each $x\in X$.

Theorem 1. A and B are two IFSs, and then we have: If $A\subseteq B$ then for each k (k=2,3) we have:

$$IAM_k(A)\leq IAM_k(B), IGM_k(A)\leq IGM_k(B).$$

Proof: $A\subseteq B\leftrightarrow \mu_A(x)\leq\mu_B(x),\nu_A(x)\geq\nu_B(x),$

$$\rightarrow \mu_A(x)-\nu_A(x)\leq\mu_B(x)-\nu_B(x).$$

So we have:

$$IAM_2(A)\leq IAM_2(B), IGM_2(A)\leq IGM_2(B).$$

And we also have:

$$A\subseteq B\leftrightarrow 1-\mu_A(x)\geq 1-\mu_B(x),1-\nu_A(x)\leq 1-\nu_B(x).$$

Therefore we have:

$$IAM_3(A)\leq IAM_3(B), IGM_3(A)\leq IGM_3(B).$$

Definition 4. A is an IFS over universe X, $A=\{<x, \mu_A(x), \nu_A(x)>|x\in X\}$, the complement of A is defined by: $A'=\{<x, \nu_A(x), \mu_A(x)>|x\in X\}$ for each $x\in X$.

Theorem 2. A is an IFS as mentioned above, then $IAM_k(A)+IAM_k(A')=1$.

Proof: $$IAM_3(A)=\sum_{x\in X} w_A(x)\frac{1-\nu_A(x)}{2-\mu_A(x)-\nu_A(x)},$$
$$IAM_3(A')=\sum_{x\in X} w_A(x)\frac{1-\mu_A(x)}{2-\mu_A(x)-\nu_A(x)},$$
$$\rightarrow IAM_3(A)+IAM_3(A')=1.$$

$$IAM_2(A)=\sum_{x\in X} w_A(x)\frac{1+\mu_A(x)-\nu_A(x)}{2},$$
$$IAM_3(A')=\sum_{x\in X} w_A(x)\frac{1-\mu_A(x)+\nu_A(x)}{2},$$
$$\rightarrow IAM_2(A)+IAM_2(A')=1.$$

We can also obtain the same conclusion for each $p>0$ and for each IFS A.

According to theorem 2, it is easy to get theorem 3.

Theorem 3. A is an IFS over universe X, then:

$$IAM_k(A)=0.5 \text{ iff } \mu_A(x)=\nu_A(x),$$
$$IAM_k(A)<0.5 \text{ iff } \mu_A(x)<\nu_A(x),$$
$$IAM_k(A)>0.5 \text{ iff } \mu_A(x)>\nu_A(x).$$

According to formula (9), we get theorem 4.

Theorem 4. Let A be an IFS over universe X, then it is easy to prove that for each k (k=2,3) , we have:

$IGM_k(A)=0$ if and only if there is $x_i\in X$, $\mu_A(x_i)=0, \nu_A(x_i)=1$.

$IGM_k(A)=1$ if and only if for each $x_i\in X$, $\mu_A(x_i)=1, \nu_A(x_i)=0$.

Comparing formula (8) and formula (9), it is concluded that if the difference among all the basic indexes $I_k(A(x))$ (for $x\in X$) is smaller, then $IGM_k(A)$ will be larger.

Applied to Practical Teaching Evaluation

In the following, the average indexes of IFS above will be applied to practical teaching evaluation. The numerical example is from references (Xu, 2007; Zhang et al., 2012, 2013). Considering the specialty of the practical teaching for the humanities and social sciences professionals, we use three attributes to make decision: homework assignments, investigation report, and classroom exercises.

Example 1. A teacher wants to evaluate the effect of the students who study a pratice course on humanities and social sciences, such as surveys, psychology, linguistics etc. Five excellent students A_i, (i=1, 2, 3, 4, 5) will be sorted. Assume that three attributes C_1(homework assignments), C_2(practice investigation report), and C_3(classroom exercises) are taken into consideration, the weight vector of the attributes C_j (j=1,2,3) is $w=(0.3,0.5,0.2)^T$. Suppose that the data show the excellent degree of the students, and the characteristics of the options A_i(i=1,2,3,4,5) are shown by IFS in the references (Xu, 2007; Zhang et al., 2012). The data are given as follows:

$A_1 = \{<C_1, 0.2, 0.4>, <C_2, 0.7, 0.1>, <C_3, 0.6, 0.3>\}$,

$A_2 = \{<C_1, 0.4, 0.2>, <C_2, 0.5, 0.2>, <C_3, 0.8, 0.1>\}$,

$A_3 = \{<C_1, 0.5, 0.4>, <C_2, 0.6, 0.2>, <C_3, 0.9, 0>\}$,

$A_4 = \{<C_1, 0.3, 0.5>, <C_2, 0.8, 0.1>, <C_3, 0.7, 0.2>\}$,

$A_5 = \{<C_1, 0.8, 0.2>, <C_2, 0.7, 0>, <C_3, 0.1, 0.6>\}$.

We will compare the results calculated by conventional average indicators of IFS (Xu, 2007) with the results calculated by the average indexes of IFS.

TABLE 1 RESULTS FROM AVERAGE INDICATORS OF IFS

Average Indicators	Decision-making Ranking on all the students
I_{Xu1}	$A_3 \succ A_4 \succ A_2 \succ A_5 \succ A_1$
I_{Xu2}	$A_3 \succ A_2 \succ A_4 \succ A_5 \succ A_1$
I_{Xu3}	$A_3 \succ A_4 \succ A_5 \succ A_2 = A_1$
I_{Xu4}	$A_3 \succ A_4 \succ A_5 \succ A_2 \succ A_1$
I_M	$A_3 = A_4 \succ A_5 \succ A_2 = A_1$
I_{NM}	$A_2 = A_5 \succ A_3 \succ A_1 \succ A_4$
I_{CT}	$A_5 \succ A_3 \succ A_4 \succ A_2 \succ A_1$
I_{HC}	$A_4 \succ A_3 \succ A_5 \succ A_1 \succ A_2$

From formulas (2), we obtain the results as follows:

$$I_M(A_1)=0.3\times0.2+0.5\times0.7+0.2\times0.6=0.53,$$
$$I_M(A_2)=0.53, I_M(A_3)=0.63, I_M(A_4)=0.63, I_M(A_5)=0.61.$$
$$I_{NM}(A_1)=0.3\times0.4+0.5\times0.1+0.2\times0.3=0.23,$$
$$I_{NM}(A_2)=0.18, I_{NM}(A_3)=0.22, I_M(A_4)=0.24, I_{NM}(A_5)=0.18.$$

Since $I_M(A_3)=I_M(A_4)>I_M(A_5)>I_M(A_1)=I_M(A_2)$ and $I_{NM}(A_2)=I_{NM}(A_5)<I_{NM}(A_3)<I_{NM}(A_1)<I_{NM}(A_4)$, we get $A_3 \succ A_2 \succ A_1$ and $A_3 \succ A_4$. For example, from the membership degree $I_M(A_5)>I_M(A_1)=I_M(A_2)$ and the non-membership degree $I_{NM}(A_5)=I_{NM}(A_2)<I_{NM}(A_1)$, we obtain $A_5 \succ A_2 \succ A_1$. Hence, either A_5 or A_3 are the optimal decision-making.

From formulas (3-4), we obtain the results as follows:

$$I_{CT}(A_1)=0.3\times(0.2-0.4)+0.5\times(0.7-0.1)+0.2\times(0.6-0.3)=0.3,$$
$$I_{CT}(A_2)=0.35, I_{CT}(A_3)=0.41, I_{CT}(A_4)=0.39, I_{CT}(A_5)=0.43.$$
$$I_{HC}(A_1)=0.3\times(0.2+0.4)+0.5\times(0.7+0.1)+0.2\times(0.6+0.3)=0.76,$$
$$I_{HC}(A_2)=0.71, I_{HC}(A_3)=0.85, I_{HC}(A_4)=0.87, I_{HC}(A_5)=0.79.$$

According to the results above and the results in Xu (2007), we have the results in Table 1.

Considering the average indicator of membership degree and the average indicator of non- membership degree, we should have $A_5 \succ A_2 \succ A_1$ and $A_3 \succ A_4$. Thus, the indicator $\mathbf{I_{Xu4}}$ and $\mathbf{I_{CT}}$ are better than the others.

From formulas (10-11), we obtain the results as follows, and Table 2 is established:

$$IAM_3(A_1)=0.3\times\frac{1-0.4}{2-0.2-0.4}+0.5\times\frac{1-0.1}{2-0.7-0.1}$$
$$+0.2\times\frac{1-0.3}{2-0.6-0.3}=0.631,$$
$$IAM_3(A_2)=0.643, IAM_3(A_3)=0.679,$$
$$IAM_3(A_4)=0.68, IAM_3(A_5)=0.686.$$
$$IAM_2(A_1)=0.3\times\frac{0.2+1-0.4}{2}+0.5\times\frac{0.7+1-0.1}{2}$$
$$+0.2\times\frac{0.6+1-0.3}{2}=0.65,$$
$$IAM_2(A_2)=0.675, IAM_2(A_3)=0.705,$$
$$IAM_2(A_4)=0.695, IAM_2(A_5)=0.715.$$
$$IGM_3(A_1)=(\frac{1-0.4}{2-0.2-0.4})^{0.3}+(\frac{1-0.1}{2-0.7-0.1})^{0.5}$$
$$+(\frac{1-0.3}{2-0.6-0.3})^{0.2}=0.614,$$
$$IGM_3(A_2)=0.637, IGM_3(A_3)=0.668,$$
$$IGM_3(A_4)=0.653, IGM_3(A_5)=0.648.$$
$$IGM_2(A_1)=(\frac{0.2+1-0.4}{2})^{0.3}+(\frac{0.7+1-0.1}{2})^{0.5}$$
$$+(\frac{0.6+1-0.3}{2})^{0.2}=0.623,$$
$$IGM_2(A_2)=0.67, IGM_2(A_3)=0.692,$$
$$IGM_2(A_4)=0.661, IGM_2(A_5)=0.653.$$

TABLE 2 RESULTS FROM AVERAGE INFEXES OF IFS

Average Indixes	Decision-making Ranking on all the students
I_{AM3}	$A_5 \succ A_4 \succ A_3 \succ A_2 \succ A_1$
I_{AM2}	$A_5 \succ A_3 \succ A_4 \succ A_2 \succ A_1$
I_{GM3}	$A_3 \succ A_4 \succ A_5 \succ A_2 \succ A_1$
I_{GM2}	$A_3 \succ A_2 \succ A_4 \succ A_5 \succ A_1$

For the conventional average indicators (Table 1), it is well known that I_{Xu4} and I_{CT} satisfy $A_5 \succ A_2 \succ A_1$ and $A_3 \succ A_4$. A_3 is the optimal decision for four methods presented by Xu in 2007. However, A_5 will be the optimal decision when we make use of I_{CT}. From Table 2, since IAM_3 does not satisfy $A_3 \succ A_4$ and IGM_2 does not satisfy $A_5 \succ A_2 \succ A_1$, IAM_2 and IGM_3 are better than them. Furthermore, from Table 2, it is indicated that the optimal decision of IAM_2 is A_5, which is the same as I_{CT}. The optimal decision of IGM_3 is A_3, which is the same as I_{Xu4}. The optimal decision of IAM_3 is also A_5, which is the same as I_{CT}. The optimal decision of IGM_2 is also A_3, which is the same as I_{Xu4}.

Taking the definitions of A_5 and A_3 into account, we have A_5 = {<C_1, 0.8, 0.2>, <C_2, 0.7, 0. >, <C_3, 0.1, 0.6>} and A_3 = {<C_1, 0.5, 0.4>, <C_2, 0.6, 0.2>, <C_3, 0.9, 0>}. We have $A_5 > A_3$ for attribute C_1 and attribute C_2 while $A_5 < A_3$ for attribute C_1, which means that A_5 is more excellent than A_3 in the homework assignments and in the practice investigation report though the performance of A_5 in classroom exercises is undesirable. Considering that homework assignments and practice investigation report are more important than classroom exercises according to the weights themselves, A_5 should be the best student. In 2007, Xu applied four kinds of distance measures to make decisions, only Xu4 method satisfies the basic conditions, then draw a conclusion that A_3 is the optimal decision-making using four average indicators. In this paper, we use some conventional average indicators and some novel average indexes of IFS to make decisions, and it is concluded that I_{CT}, IAM_2 and IGM_3 satisfy the basic conditions. However, when applying these indicators of IFS to make decisions, we reveal a potential optimal decision-making A_5 and the reason for A_5. Moreover, we use only four simplest measures when p=1 to make decision in this paper, and the results are the same as those from conventional evaluation methods of IFS, and researchers can set more value from parameter p to evaluate the students in practice.

Conclusions

A novel average index method of IFS derived from Xu's relative average indicators proposed in this paper has been applied to a practical teaching evaluation problem for the students from the humanities and social sciences professionals in university. The results from the average index method involve all the best results from the conventional average indicators, and also it is more simple than Xu's methods.

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