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Application of fuzzy logistic regression in modeling the severity of autism spectrum disorder

Ali Behnampour[1], Enayatolah Bakhshi[2], Akbar Biglarian[3*]

1. Department of Biostatistics, University of Social Welfare and Rehabilitation Sciences, Tehran, Iran.
2. Department of Biostatistics, University of Social Welfare and Rehabilitation Sciences, Tehran, Iran.
3 Department of Biostatistics, Social Determinants of Health Research Center, University of Social Welfare and Rehabilitation Sciences, Tehran, Iran.

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****Correspondence:***

Akbar Biglarian, Department of Biostatistics, Social Determinants of Health Research Center, University of Social Welfare and Rehabilitation Sciences, Tehran, Iran.

abiglarian@uswr.ac.ir

Abstract

Background and objectives: Autism spectrum disorder (ASD) is a childhood neurodevelopmental disorder and according to DSM-5 classification, its severity includes three levels: requiring support, requiring substantial support, and requiring very substantial support. This classification is unclear from a possible perspective and from a fuzzy point of view; it has a degree of uncertainty. The purpose of this study is to predict the severity of autism disorder by fuzzy logistic regression.

Methods: In this cross-sectional study, 22 children with ASD which referred to the rehabilitation centers of Gorgan in 2017 were used as a research sample. Therapist's viewpoint about the severity of the disorder that is measured by linguistic terms (low, moderate, high) was considered as fuzzy output variable. In addition, to determine the prediction model for the severity of autism, a fuzzy logistic regression model was used. In this sense parameters were estimated by least square estimations (LSE) and least absolute deviations (LAD) methods and then the two methods were compared using goodness-of-fit index.

Results: The age of children varied from 6 to 17 years old with mean of 10.44± 3.33 years. Also, the goodness-of-fit index for the model that was estimated by the LAD method was 0.0634, and this value was less than the LSE method (0.1255). The estimated model by the LAD indicates that with the constant of the values of other variables, with each unit increase in the variables of age, male gender, raw score of stereotypical movements, communication and social interaction subscales, possibilistic odds of severity of autism disorder varied about 0.67 (decrease), 0.362 (decrease), 0.098 (increase), 0.019 (increase) and 0.097 (increase) respectively.

Conclusion: The LAD method was better than LSE in parameter estimation. So, the estimated model by this method can be used to predict the severity of autism disorder for new patients who referred to rehabilitation centers and according to predicted severity of the disorder, proper treatments for children can be initiated.

Keywords: Fuzzy logistic regression; Possibilistic odds; Linguistic term; Autism; Autism Spectrum Disorder

Introduction

Autism Spectrum Disorder (ASD) is one of the neurodevelopmental disorders which characterized by severe deficits and pervasive impairment in multiple areas of development including impairment in reciprocal social interaction, impaired communication, and the presence of stereotyped behaviors, interests, and activities (1). This disorder is recognized as the most serious and at the same time the most unknown childhood disorder (2, 3). For the first time in 1943, the Austrian psychiatrist, Leo Conner, described and introduced children who, from the first year of their lives, constantly avoided any contacts and in their behavior, there were signs of features such as autism, repetition or verbal echoes, consistency, and lack of eye contact (4-6).

Autism spectrum disorder (autism) includes, Autistic disorder (Some people with autism spectrum disorder with common IQ are known as patients with high functioning autism HFA), Asperger's syndrome (there is controversy about the validity of the distinction between Asperger's syndrome and high functioning autism), Rett syndrome, Childhood disintegrative disorder and Pervasive developmental disorders not otherwise specified PDD-NOS (also known as abnormal autism) (7). The common feature of these five disorders is their occurrence in early childhood and the violation of social relations and functioning which recognized as the most important feature of all these disorders (8).

Studies illustrates an increasing prevalence of this disorder. According to the Centers for Disease Control and Prevention (CDC) prevalence of this disorder reported one out of 150, one person in 110, one per 88 people and one in 68 in 2002, 2006, 2008 and 2014, respectively (9-11). Prevalence studies in Iran also indicate growth in the number of children dealing with autism. Bozorgnia, Malekpour, and Abedi reported the prevalence of this disorder 12.15 and 9.97 per 10,000 children in Isfahan and Shahre-kord, respectively (12). Samadi et al. reported the prevalence of autism in Iran, 6.26 per 10,000 children in 2007 (13) and 95.2 per 10,000 children in 2014 (14). It is also worth noting that men are more likely to suffer this disorder, 6 against 1, compared to women (15). Given the many problems that this disorder can cause for the child, family and society and its increasing prevalence, the necessity of early screening and diagnosis and timely interventions are of particular importance (16). One of the major problems of children enduring autism spectrum disorder is their defection in social communication. Failure in normal social communication can have a negative impact on other aspects of growth, including joint attention. The close relationship between impairment in joint attention and deficits in other skills underlines the importance of this ability. Joint attention skills predict other skills such as language skills and social behaviors, social-emotional comprehension, symbolic games, the theory of mind, and social cognition in children with autism (17).

Since 1980 which autism disorder was first recognized as a separate category, until 2013 when the fifth edition of the DSM-5 Diagnostic and Statistical Manual of Mental Disorders (DSM-5) was published by the American Psychiatric Association, vast changes have occurred in the field of autism. The main criticism of the earlier version of the DSM was that it lacked a discriminatory classification of transparency. Some studies demonstrate that in many disorders the distinction between major and mild symptoms is related to "level", not "type" (18). Because of that and also due to problems in distinguishing autism disorder, Asperger's disorder, Rett's syndrome, and Childhood disintegrative disorder, the DSM-5 eliminated all these disorders and classified them under the so-called "autism spectrum disorder (autism)" (1). Diagnostic and Statistical Manual of Mental Disorders-Fifth Edition has introduced three levels of severity for autism: Level 1: Requiring support; Level 2: Requiring substantial support; Level 3: Requiring very substantial support.

Diagnosis of Autism Spectrum Disorder is a complex process that requires a standard set of information through the observation of the child and interviewing parents as well as other information about the child's performance. Standardized and validated tools can greatly help professionals in the process. Early detection of autism spectrum disorders is an important issue in autism research. The importance of this issue has enhanced, especially after the publication of studies showing that early intervention and treatment of autism spectrum disorders are associated with superior outcomes. In other words, early detection of autism spectrum disorders increases the possibility of receiving relevant and focused intervention services based on the specific educational and clinical needs of the child (19). Researchers' attention to treatment has led them to look for precise tools to diagnose autism disorder. For this purpose, several diagnostic tools have been developed, including the GARS as one of the most important ones. This test was developed as a valid test by Gilliam in 1994 and its reliability in the range of acceptability has been accepted (20).

"Indeed, the complexity of biological systems may force us to alter in radical ways our traditional approaches to the analysis of such systems. Thus, we may have to accept as unavoidable a substantial degree of fuzziness in the description of the behavior of biological systems as well as in their characterization. " Zadeh said in 1969 (21). He further stated the main use of linguistic variables and fuzzy algorithms in fields such as economics, management, artificial intelligence, psychology, linguistics, medicine and biology (22).

To model the relationships between variables whose observations are ambiguous, conventional statistical models based on accurate observations and some distributional assumptions cannot be used. Therefore, fuzzy sets can be used to model, describe, and analyze the relationships between such variables. Therefore, fuzzy set theory can be used as an alternative to modeling, describing, and analyzing the relationships between such variables. Since the introduction of fuzzy set theory, its application has been expanding in vast fields of statistics, many of which are conceivable in applied medical research, including: Fuzzy clustering, fuzzy discriminant analysis (23), fuzzy regression (24, 25), fuzzy approach disease detection (26), and modeling the appearance and transmission of latent diseases (27).

Virtually most studies on fuzzy regression have been performed on linear models, and nonlinear models have rarely been investigated in the fuzzy field. Logistic regression model is known as one of the most famous nonlinear models which widely used in medical sciences and social studies. In this model, the values of the response variable can be discrete or qualitative, and accurate observations must be used to fit the model. Non-precise or vague observations occurred frequently in practical situations, especially in medical studies such as cases measured by linguistic terms rather than numbers, and thus the assumptions of the logistic regression model are violated or cannot be investigated. When data set includes ambiguous data which cannot be expressed by exact real number, fuzzy logistic regression could be an alternative choice (28). The purpose of this study is to fit a model to determine the severity of autism disorder using fuzzy logistic regression.

Material and methods

In this cross-sectional study, 22 children with ASD which referred to the rehabilitation centers of Gorgan in 2017 were used as research samples, who were selected in the census. Their parents or therapists were asked to intently complete the Persian version of the Gilliam Autism Rating Scale (GARS) for these children. Gender, age (year) and raw score for each of the stereotypical movements, communication and social interaction subscales were considered as the crisp input variables. Also, another therapist's opinion, who evaluated individuals, was recorded as the severity of the disorder as a fuzzy response variable. The therapist was asked to assign a severity of the disorder to each case using linguistic terms (low, moderate, high). After evaluation, 3 children were excluded due to lack of communication subscale score (because of speech inability), and one child as a result of missed social interaction subscale score, therefore the number of subjects declined to 18 individuals.

The questioner used in this study was the Persian version of the Gilliam Autism Rating Scale (GARS), which Cronbach's alpha coefficient of 0.90 for stereotypical movements, 0.89 for communication, and 0.93 for social interaction is reported (29).

In the present study, the fuzzy logistic regression with crisp input and fuzzy output was employed to analyze the data. In order to evaluate the goodness of fit of the model, Measure of performance based on fuzzy distance (MP) is used. In the following, details of fuzzy logistic regression are explained for further elucidation.

Fuzzy Logistic Regression:

Let μ_i = Poss (Y_i = 1), i = 1,…, m, be the possibility of characteristic 1 or success, for the ith case. The possibility of success for the preferred characteristic is defined by a linguistic term, μi ∈ (low, moderate, high). Appropriate fuzzy numbers can be defined by an expert for each term of the linguistic variable. These terms should be defined in such a way that the union of their supports cover the whole range of (0, 1). Then the ratio $\mu_i / 1-\mu_i$ is considered as possibilistic odds of the ith case, which detects the possibility of success relative to the possibility of non success.

For modeling the possibilistic odds based on a set of crisp explanatory variables, the observations for the ith case are considered as $x_{ij}(i = 1,2, \dots, m; j = 0,1, \dots, n)$. The fuzzy logistic regression model is, therefore, as follows:

$$\widehat{W}_i = ln(\mu_i/1-\mu_i) = \sum_{j=0}^{n} A_j x_{ij}\,; \quad x_{i0} = 1\ ,\ i = 1,2,\dots,m \qquad (1)$$

where $A_j = (l_j, c_j, r_j)$ is a triangular fuzzy number.

For example triangular fuzzy numbers that are defined for the possibility of success μ= (Low, Moderate, High) are given in (2) and are shown in Fig. 1.

μ = (Low, Moderate, High)
Low = (0.01, 0.02, 0.3)
Moderate = (0.25, 0.5, 0.75)
High = (0.7, 0.98, 0.99)

(2)

The fuzzy regression model in which input data are non-fuzzy and output data are fuzzy, is expressed as the following equation:

$$\widehat{W}_i = \sum_{j=0}^{n} A_j x_{ij}\,; \quad x_{ij} \geq 0\ , x_{i0} = 1,\ \ i = 1,2,\dots,m \qquad (3)$$

The regression coefficients are not necessarily symmetric triangular fuzzy numbers. l_j is the left endpoint, r_j is the right endpoint, and c_j is the mode of A_j (30).

When the expert assigns a linguistic term like μ = (Low, Moderate, High) as the possibility of success for the preferred characteristic, then the logarithm transformation of possibilistic odds, $W_i = ln\left(\frac{\mu_i}{1-\mu_i}\right)\ i = 1,2,\dots,m$ are considered as the observed outputs. The membership function of these observed outputs can be calculated from the defined membership function of μ_i (2) and extension principle as follows:

$$w_i(y) = \underset{\forall x: f(x)=y}{Sup}\ \mu_i(x) \qquad (4)$$

In which $f(x) = ln\frac{x}{1-x}\quad 0 < x < 1$ is a one-to-one function. So, there is one and only one $x \in (0,1)$ such that $ln\frac{x}{1-x} = y$, therefore,

$$w_i\left(y = ln\frac{x}{1-x}\right) = \mu_i\left(\frac{exp(x)}{1+exp(x)}\right).$$

The regression parameters were estimated using Least absolute deviations (LAD) and Least squares estimation (LSE) (32). It should be noted that the method of estimating the regression parameters and calculating the goodness of fit criteria was given in the appendix.

Results

Participants in the study included 18 children ages 6 to 17. The mean ± SD of children's age was 10.44 ± 3.33 years. Approximately %22 of the children were girls. Gender, age (year) and raw score for each of the stereotypical movements, communication and social interaction subscales were considered as the crisp input variables and another therapist's opinion, who evaluated individuals, was recorded as the severity of the disorder as a fuzzy response variable in linguistic terms

(Low, Moderate, High). Participants data are shown in Table 1.

To develop the relationship between possibilistic odds of the severity of the disorder and the above-mentioned factors, the proposed model is fitted:

$$\widehat{W}_i = ln(\mu_i/1-\mu_i) = \sum_{j=0}^{5} (l_j, c_j, r_j)x_{ij}, \quad (5)$$

Where x_{i1}= Gender, x_{i2}= Age, x_{i3}= Stereotypical movements, x_{i4}= Communication and x_{i5}= Social interaction. The results of LAD and LSE are provided as follows.

LAD:

$$\begin{aligned}\hat{W}_i = &(0.367, 0.367, 1.568)x_{i0} + (-0.082, -0.076, -0.076)x_{i1} + \\ &(-0.362, -0.362, -0.358)x_{i2} + (0.098, 0.098, 0.098)x_{i3} + \\ &(0.019, 0.019, 0.019)x_{i4} + (0.085, 0.097, 0.097)x_{i5}\end{aligned} \quad (6)$$

LSE:

$$\begin{aligned}\hat{W}_i = &(2.528, 2.528, 2.528)x_{i0} + (-0.786, -0.786, -0.786)x_{i1} + \\ &(-0.493, -0.493, -0.377)x_{i2} + (0.053, 0.053, 0.053)x_{i3} + \\ &(0.097, 0.097, 0.097)x_{i4} + (0.049, 0.049, 0.049)x_{i5}\end{aligned} \quad (7)$$

In summary, the estimated positive coefficients in the fuzzy logistic model indicate that the correspondence variable is related to an increase in possibilistic odds of struggling with a severe disorder, and negative coefficients indicate that the correspondence variable is related to a decrease in possibilistic odds of tussling with an intensive disorder.

The results of LAD and LSE estimation approaches and goodness of fit indices are given in Table 2.

Now, suppose there is a 12 years old boy with ($x_{i3} = 15,\ x_{i4} = 12,\ x_{i5} = 26$). Then, according to model 6, the possibilistic odds of intense disorder for this person is obtained as:

This means that $\widehat{W}_{new}$ = (−0.23,0.09,1.34), i.e., the logarithm of possibilistic odds for this case, is about 0.09 (a fuzzy number). And now, to calculate the estimated possibilistic odds using the extension principle we have:

$$\exp\left(\hat{W}_{New}(x)\right) = \frac{\mu_{New}}{1-\mu_{New}}(x) = \begin{cases} 1-\dfrac{0.09-\ln(x)}{0.324} & 0.79 \le x \le 1.09 \\ 1-\dfrac{\ln(x)-0.09}{1.249} & 1.09 < x \le 3.82 \end{cases} \tag{8}$$

$$\hat{\mu}_{New}(x) = \hat{W}_{New}(ln\frac{x}{1-x}) = \begin{cases} 1-\dfrac{0.09-\ln(\frac{x}{1-x})}{0.324} & 0.44 \le x \le 0.52 \\ 1-\dfrac{\ln\left(\frac{x}{1-x}\right)-0.09}{1.249} & 0.52 < x \le 0.79 \end{cases} \tag{9}$$

This means that the possibilistic odds of severe disorder of this patient is “about 0.52".

Table 1: Fuzzy observations in Autism disorder and the values of related factors

No.	Gender	Age	Stereotypical movements	Communication	Social interaction	Possibility of disorder μ_i
1	Male	6	18	4	31	High
2	Male	6	18	15	22	Moderate
3	Female	15	21	23	22	Moderate
4	Male	13	18	35	25	High
5	Male	15	22	23	27	Moderate
6	Female	10	7	3	11	Low
7	Male	10	24	28	16	Moderate
8	Male	11	22	38	19	Moderate
9	Male	15	10	13	13	Low
10	Male	17	12	21	20	Low
11	Male	6	14	14	31	High
12	Female	9	21	13	25	High
13	Male	9	35	18	33	High
14	Female	8	8	8	9	Moderate
15	Male	10	31	12	32	Moderate
16	Male	10	10	9	3	Moderate
17	Male	10	24	14	8	Moderate
18	Male	8	24	11	0	Moderate

Table 2: The estimations and goodness-of-fit values for the Autism Data

Estimates	LAD	LSE
(l_0, c_0, r_0)	(0.37 , 0.37 , 1.57)	(2.53 , 2.53 , 2.53)
(l_1, c_1, r_1)	(-0.08 , -0.07 , -0.07)	(-0.79 , -0.79 , -0.79)
(l_2, c_2, r_2)	(-0.36 , -0.36 , -0.35)	(-0.49 , -0.49 , -0.37)

(l_3, c_3, r_3)	(0.1 , 0.1 , 0.1)	(0.05 , 0.05 , 0.05)
(l_4, c_4, r_4)	(0.02 , 0.02 , 0.02)	(0.097 , 0.097 , 0.097)
(l_5, c_5, r_5)	(0.1 , 0.1 , 0.1)	(0.05 , 0.05 , 0.05)
M_p	0.0634	0.1255

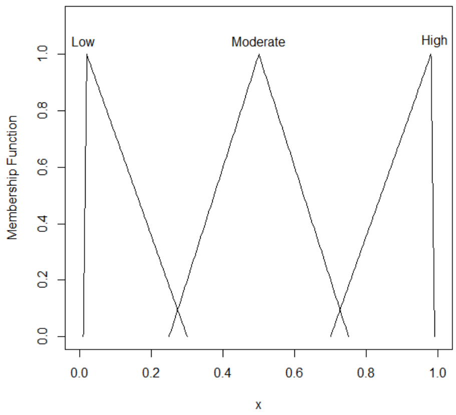

Fig 1: Suggested definitions for μ_i

Discussion

Autism Spectrum Disorder (ASD) recognized as the most serious and at the same time the most unknown childhood disorder (2, 3). Usually, Autism occurs in the early years of childhood and the violation of social relations and functioning is recognized as the most serious feature of this disorder (8). Given the various problems that this disorder can cause for the child, family and society and its increasing prevalence, the necessity of early screening and diagnosis and timely interventions are of particular importance (16), because it increases the possibility of receiving relevant and focused intervention services based on the specific educational and clinical needs of the child (19). In addition, some studies demonstrate that in many disorders the distinction between major and mild symptoms is related to "level", not "type" (18). Therefore, the use of tools such as GARS for the diagnostic and therapeutic purposes of this disorder would be useful (20, 29).

Nevertheless, caution should be exercised in classifying the severity of the disorder, which is based on linguistic terms, and then analyzing it, which is commonly used by logistic regression, since fuzzy logistic regression should be used if the assumptions of the logistic regression are not fulfilled due to the ambiguous nature of the linguistic terms or the values of the variables. Also in regression analysis, in the case when we have outliers, it is important to find estimation approaches which are robust to outliers (30). Choi and Buckly investigated the fuzzy regression analysis based on LAD approach, using α-cuts of fuzzy numbers (31). Taheri and Kelkinnama introduced two methods for constructing fuzzy regression model based on the LAD method, for crisp input-fuzzy output and fuzzy input-fuzzy output data (32, 33). Namdari et al. developed the LAD method for modeling and compared it with the LSE method and also represented new goodness of fit indices called Measure of performance based on fuzzy distance (Mp) (30).

In the present research, Least-squares estimation (LSE) and least absolute deviations (LAD) methods were exerted to estimate regression parameters of autism spectrum disorder data using fuzzy logistic regression. In this study, the values of Mp to compare the efficiencies of different fitting methods suggested that, LAD is much more efficient than LSE, which is in line with the results of Namdari's study (30).

Conclusion

When the severity of a disorder, such as the autism spectrum disorder, have levels based on linguistic terms, fuzzy logistic regression provides an appropriate alternative tool for modeling in a more flexible environment. In the current study, the goodness-of-fit criterion for the LAD (0.0634) and LSE (0.1255) methods indicated that the fuzzy logistic regression model was suitable for both estimation methods, yet the model estimated by LAD method is a more appropriate model because of the lower numerical value of goodness of fit than LSE method. The models derived from this study could be helpful in order to more accurately determine the severity of the disorder in young children, who are referred to rehabilitation centers, to begin the most proper treatment as soon as possible.

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Declarations

Conflict of interest

None

Authors' contributions

All authors contributed equally to this work.

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Appendix

Estimation of the model parameters

In order to minimize the difference among observed and predicted fuzzy output data, which is the purpose of fuzzy regression, α-cuts of the observed and predicted fuzzy outputs can be utilized. Therefore, the α-cuts of the logarithmic transformation of observed odds $W_i(\alpha)$ can be calculated. For example consider the following membership function for the possibility of success for the ith observation $\mu_i = (l_{\mu_i}, m_{\mu_i}, r_{\mu_i})$, then its α-cuts would be as

$$\mu_i(\alpha) = [l_{\mu_i}(\alpha), r_{\mu_i}(\alpha)] = [m_{\mu_i} - (1-\alpha)(m_{\mu_i} - l_{\mu_i}), m_{\mu_i} + (1+\alpha)(r_{\mu_i} - m_{\mu_i})] \quad (1)$$

In order to derive $W_i(\alpha)$, we have

$$W_i(\alpha) = [l_{w_i}(\alpha), r_{w_i}(\alpha)] = [-ln(\frac{1-l_{\mu_i}(\alpha)}{l_{\mu_i}(\alpha)}), -ln(\frac{1-r_{\mu_i}(\alpha)}{r_{\mu_i}(\alpha)})] \quad (2)$$

The following interval is derived for the α-cuts of the logarithmic transformation of estimated odds $\widehat{W}_i(\alpha)$:

$$\hat{W}_i(\alpha) = \left[l_{\hat{W}_i}(\alpha), r_{\hat{W}_i}(\alpha)\right] = \sum_{j=0}^{p}\left[l_{A_j}(\alpha), r_{A_j}(\alpha)\right]x_{ij} = \left[\sum_{j=0}^{p} l_{A_j}(\alpha)x_{ij}, \sum_{j=0}^{p} r_{A_j}(\alpha)x_{ij}\right] \quad (3)$$

Least absolute deviations (LAD):

The LAD estimators $\bar{l}_{A_j}(\alpha)$ and $\bar{r}_{A_j}(\alpha)$ which satisfy the following conditions can be derived:

$$\sum_{i=1}^{n} \left| l_{W_i}(\alpha) - \sum_{j=0}^{p} l_{A_j}(\alpha)x_{ij} \right| = min! \quad (4)$$

$$\sum_{i=1}^{n} \left| r_{W_i}(\alpha) - \sum_{j=0}^{p} r_{A_j}(\alpha)x_{ij} \right| = min! \quad (5)$$

Least squares estimation (LSE):

For estimating the regression parameters by LSE, (4) and (5) will be replaced by

$$\sum_{i=1}^{n} \left(l_{W_i}(\alpha) - \sum_{j=0}^{p} l_{A_j}(\alpha)x_{ij} \right)^2 = min! \quad (6)$$

$$\sum_{i=1}^{n} \left(r_{W_i}(\alpha) - \sum_{j=0}^{p} r_{A_j}(\alpha)x_{ij} \right)^2 = min! \quad (7)$$

Measure of performance based on fuzzy distance (M_P):

In classical regression analysis, mean absolute percentage error is used for evaluating the goodness-of-fit of regression models. In fuzzy environment, based on the difference between the membership value of the observed fuzzy number and the estimated fuzzy number, we can use the mean absolute percentage error as a measure of goodness-of-fit. But, when the observed and the predicted value are not overlapped, this measure of performance has a weakness. In this case, the value of the measure of performance will be the same regardless of the amount of distance between the observed and its estimation. In order to overcome this problem, the following modified Measure of Performance based on Fuzzy Distance (M_p) will be used:

$$M_p = \frac{1}{n}\sum_{i=0}^{n} d\left(W_i, \widehat{W}_i\right) \quad (8)$$

$$d\left(W_i, \widehat{W}_i\right) = \frac{\int \left|\mu_{w_i}(x) - \mu_{\widehat{W}_i}(x)\right| dx}{\int \mu_{w_i}(x)\,dx} + h_d\left(W_i(0), \widehat{W}_i(0)\right)$$

Where*:*

$h_d(A, B) = inf_{a \in A}\, inf_{b \in B} |a - b|$. (32)