استعمال المحاكاة في الانحدار الضبابي

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الملخص :

يواجه المحلل جزءا من المشكلات عند اختبار دقة النموذج لتقدير معلمات نموذج الانحدار الضبابي ، لذا تم إنشاء متغيرات تتوزع توزيع طبيعي لتقليل خطأ التنبؤ عـــن طريــق استعمال الطريقة الأكثر شيوعا وهي طريقة (Box-Muller) ، والتي تعتمد على استراتيجيـــة إنشاء متغيرات غيـــر منتظمة تتوزع توزيع قياسي U (0,1) ، وبعد ذلك يتم تغيير هذه المتغيرات إلى متغيرات عشوائية حرة تأخذ بعد التشتت الطبيعي القياسي لتقييم معلمات البرهان وبالترتيب لتقليل خطأ التوقع هو الخطأ التربيعي العادي بين التركيزات المتوقعة والحقيقية التي توضح الدقة وتظهر الغموض التي تتحدث عن الضعف في إظهار التوقعات. كلما انخفضت هذه القيم ، كان أداء العرض متفوقا من حيث الدقة والجودة التي لا تتزعزع.

الكلمات المفتاحية : الانحدار الضبابي، نموذج Tanaka، المربعات الصغرى الضبابية، بيز الضبابية، العزوم الضبابية، المحتمل الضبابي، Box-Muller، المحاكاة .

Using Simulation in Fuzzy Regression

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Abstract:

The analyst faces some difficulties in analyzing the accuracy of the model, especially when estimating the parameters of the fuzzy regression model. Therefore, variables were created and normally distributed in order to reduce prediction errors by using the most widely used and common method, which is the Box-Muller method, because it relies on the strategy of creating irregularly distributed variables. A standard distribution U $(0,1)$, and then these variables are changed to free random variables that take the standard natural dispersion dimension, which can evaluate the proof parameters and also reduce the prediction error, which is the normal squared error that exists between the expected concentrations and the real concentrations, which in turn explains the accuracy. It shows ambiguity that speaks of weakness in showing expectations. The display performance is superior in terms of accuracy and quality that does not falter as these values decrease.

Keywords: Fuzzy Regression, Tanaka Model, Fuzzy Least Squares, Fuzzy Bayesian, Fuzzy Moments, Fuzzy Probability, Box-Muller, Simulation.

1. Introduction:

The statistical analyst faces some difficulty when estimating regression functions, for example, the relationship between model parameters is ambiguous, or the model used is not specified, or when the problem does not meet the assumptions of probity regression (i.e., the regression model parameters must be constant), or when the size of the data is small, Fuzzy regression is used. Instead of using statistical regression, we also face problems that are difficult or cannot solved mathematically, because they are complex to change due to the inability of controlling the variables involved and affecting the problem. There are also statistical theorems that are difficult to be analyzed logically using complex mathematical proofs to understand.

Hence comes the role of simulation method, which represents the real reality with specific models. By simulating the model, we will achieve a degree of understanding of the real reality or the original process, and the degree of similarity between the real reality and any simulation experience depends on the extent to which the simulation model matches the real system. The experiments also feature that the simulation reduces the time when performing operations on an electronic calculator, assumes levels of variation for random errors, and chooses flexibility for different sample sizes.

In this passage, the foremost vital things that have considered within the past a long time of the subject of the current think about will tended to, concurring to the researcher's information of it:

- The study (Mohammed, 2007), included the impervious estimates of the fuzzy regression to find the estimators of the parameters of the regression model in the event of uncertainty due to Fuzzy. In addition, the method of the least squares fuzzy repetition weighted used to find the impervious estimates of the parameters of the fuzzy regression model. The standard of average squares of error used for the parameter, the model, and the relative efficiency criterion to indicate the preference of methods. It was found that the first proposed function grants the lowest average squares of error for the estimates of the parameters and the model and the highest relative efficiency in the event of a deviation in the value of the average. The second proposed function (FR3) gave the lowest average squares of error for the estimates of the features, and the model with the highest relative efficiency in the event of a deviation in the value of the random error variance from the standard normal distribution, or the error distributed in a normal logarithmic distribution. [18]
- The study included (Al-Ghannam & Al-Sabbagh, 2009), the definition of fuzzy groups and the study of fuzzy variables and

fuzzy random variables. The fuzzy regression model was estimated using the method of fuzzy least squares and after applying to the real data concerning the components of human blood, the results found that the data contain little foggy and the fuzzy model is close in its estimation to the traditional model [13].

- A study (Aziz, 2018) compared between fuzzy regression and hippocampus regression, as fuzzy regression used to calculate the proposed affiliation function, which represents the matrix of weights and through which the weight of each observation is determined representing the extent of its contributions of information to the estimation of the model parameters of the hippocampus fuzzy regression. The two methods applied to environmental variables (carbon dioxide) and economic activities (GDP, population, fossil energy consumption, and economic openness) and used the relative square scale of error, and the results were that the hippocampus fuzzy regression was better at estimating the parameters than the fuzzy regression. [6]

1− Fuzzy Linear Regression Model(F L R) [17][5]

It used to determine the ideal linear relationship between independent variables and dependent variables in an ambiguous environment. The goal of fuzzy linear regression is to model an ambiguous or inaccurate event using fuzzy model parameters. Fuzzy aggregation theory is the effective and appropriate means of formulating statistical models, as it addresses ambiguity or inaccuracy when observations are blurry and fuzzy regression estimated based on:

1. Possible Regression that uses mathematical programming in estimating depending on the existence of the object.
2. Likely Regression and uses the Fuzzy Least Squares (FLSLR) method in estimating there is a tendency that the higher the values of the illustrative variables, the wider the propagation of the response variable.

2- Fuzzy Regression Traits [12][20]

Fuzzy regression characterized by several characteristics, including:

1. Errors in fuzzy regression comes from the assumption the system structure is not determined the ambiguity in the knowledge of the model (Tanaka et al., 1982). So the deviations between the estimated values and the values of observations depend on the ambiguity and lack of identification of the parameters that cover the system composition, i.e. they arise from the system blur.
2. Fuzzy regression uses a data set as fuzzy numbers. The purpose of Fuzzy Regression is to find the phenomenon of relationship between variables vaguely and imprecisely using fuzzy functions known as Fuzzy Set Theory.

3. Fuzzy set theory is the basis of fuzzy regression, such as it defined by the function of belonging to a set of data.
4. When n of the interpreted variables are available, the fuzzy regression model is as follows:

$$Y_i = \acute{A}X$$
$$Y_i = A_\circ + A_1 X_{i1} + \cdots + A_n X_{ii} + \epsilon_i \quad .... \quad (1)$$

Whereas

Y_i : Response variable value

X=$[1, x_{i1}, \dots, x_{in}]$ Illustrative variables

$\acute{A}_\circ, \acute{A}_1, \dots, \acute{A}_n$ The vector of the fuzzy model parameters can denoted as a vector and according to the following formula:

$$\alpha = \{\alpha_\circ, \alpha_1, \dots, \alpha_n\}'$$
$$c = \{c_\circ, c_1, \dots, c_n\}'$$
$$\alpha = \{\alpha, c\}$$

α_j: The value of the mean (i.e. the center of the fuzzy parameterA_j)

c_j: Diffusion value of the fuzzy parameter

3- Methods for Estimating the Fuzzy Regression Model[19]

There are several methods for estimating the fuzzy regression model as follows:

Tanaka model: [4] [14]

The scientist (Tanaka et al., 1982) introduced this method applies that the fuzzy linear is function to determine a mysterious phenomenon. In the traditional regression, the deviations are generally between the estimated values and the observed values arising from observational errors. However, in this method the deviations depend on any determining to the structure of the system, so these deviations are fuzzy for the system parameters, as the fuzzy regression proposed by Tanaka uses fuzzy numbers. The use of fuzzy numbers improves problem modeling as the output variable (scalar and continuous) affected by inaccuracies.

5-Fuzzy Least Squares Estimators Regression (FLS Es) [23] [9] [7] [8] [1]

The statistical technique presented by scientist like,(Savic and Pedrycz, 1991), as another formula for the fuzzy linear regression method, it has confirmed its use. (Woodall, 1994). In a subsequent study, for ease of calculation, it is implemented to solve unknown parameters (fuzzy) in the regression model and is considered the most common method, as the fuzzy least squares method treats regression parameters as fuzzy numbers. The least squares method used to find the best model by minimizing the dimension between the actual value and the expected value, and is usually the sum of the squares of the differences between the upper and lower bounds of the Actual outputs (the true value). Y_iCorresponds to the optimization problem, and the parameters of the fuzzy regression model can estimated as follows:

$$(b_i^k)^T = (X^TX)^{-1}X^TAY \ \dots \ (2)$$
$$(a_i^k)^T = (X^TX)^{-1}X^TaY \ \dots (3)$$

$\hat{y}_l$: Represents the predicted value.

4– Fuzzy Bayesian Method[21][22]:

This method is of great importance in inferential statistics and in recent decades. Bayes' theory has been a viable and powerful alternative to traditional statistical perspectives. In the Bayes method, the parameters assumed to be random variables and have a prior distribution determined from the previous information and experience of similar studies, after which the previous distributions combined with the probability function to obtain the common post–density function to become the basic solution in inference for the estimate of Bayes.

To illustrate the idea for the Fuzzy Bayes method, let ($x_1, x_2, x_3, \dots., x_n$) be a random sample with a probability function with an inverse distribution of gamma (x, α, β) and π_1 (α)and π_2 (β) be the initial distribution of parameter α, β respectively, assuming the previous independent initial distribution is exponential.

5– Fuzzy Moments Method [15] [16]

This method based on finding k of the parameters, then equalizing the moment of the population with the corresponding sample moments, where we get k equations with the number of parameters, and then the required estimators obtained by solving the resulting equations.

The method of moments known as one of the simplest methods to estimate parameters in a density function. The idea of this method is to find the population moments, find the moments of the sample distribution, and then equate them to estimate the density function parameter.

6- Fuzzy Probable Regression Model [10]

The scientist Tanaka was the first to propose a Fuzzy probity Regression model that reflects the Fuzzy Relationship between the independent variables and the dependent variable. It aims to build a model that contains all the estimated data through the probable model to reduce blur to a minimum by reducing the overall differences of the fuzzy model parameters, with the data points for each sample included within a specific data interval. The regression model then improved by reducing the spread taking into account the data.

The fuzzy possible regression can expressed as follows:

$$y = A_1x_1 + \cdots \ldots \ldots . A_nx_n = A^Tx \quad \ldots (4)$$

A_n: Represents the parameters of the specified interval with the center (a_i) and propagation c_i

In a fuzzy potential regression, the specific y outputs are clear intervals.

7- Experimental side (simulation concept) [2] [3] [11]

Simulation defined as the process of representing or simulating real reality, i.e., trying to find a mirror image of any model or system without taking the model or system itself, using certain models, as we often encounter in real reality processes. Also, problems that cannot be solved mathematically or are difficult to solve, because they are complex to understand, so it is not possible to control the variables and influences present in this problem, and there are statistical theories that cannot be easily analyzed logically using mathematical proof.

Default values

Based on previous studies and published research, the following hypothetical values adopted:

$$\beta = (\beta_0, \beta_1, \beta_2, \beta_3, \beta_4) = (1.5, 2, -0.5, 0.3, 1)$$

Determine the sample size: Four sample sizes have chosen: (n=20, 50, 150)

Generate Explanatory Variables

Generate values of independent variables X_{ij} according to the standard normal distribution

$$X_{ij} \sim N(0,1) \; \forall \; i = 1, \ldots\ldots n, \quad j = 1,2,3,4 \qquad \ldots.(5)$$

For the threshold limit or segment of the affiliation function:

$$(\alpha_\circ) = (0.3, 0.4, 0.5)$$

Generate Random Error Vector

Generating random errors that are normally distributed with a mean (0) and variance σ^2, and generating variables that follow a normal distribution, using the Box−Muller method, which is the most famous and common method that relies on the method of generating random variables that are distributed with a standard distribution U(0,1), and these variables are converted into variables. Independent random distribution with a standard normal distribution according to the following:

$$Z_1 = (-2LnU_1)^{\frac{1}{2}}\ Cos(2\pi U_2)\quad ....(6)$$

$$Z_2 = (-2LnU_1)^{\frac{1}{2}}\ Sin(2\pi U_2)\quad ...(7)$$

$$Z = \frac{(Z_1 + Z_2)}{2}\quad ....(8)$$

$$\varepsilon_i = Z\,\sigma^2\quad \forall\ i = 1,2,....,n\quad ...(9)$$

Generate supported variable values

The variable (y_i) generated through the models used in simulation experiments using fuzzy regression functions in terms of illustrative variables in addition to the random error vector

Simulation Results:

The simulation experiment was conducted using three sample sizes n= 20, 50, 150, Replicates= 1000, three contrast levels $\sigma^2 = 0.5\ ,1\ ,1.5$ and cutting levels (0.3, 0.4, 0.5) for each simulation experiment.

Table (1) Fuzzy regression parameters estimated using the LS method when $\sigma^2 = 0.5$, different terms, and different sample sizes

threshold value	sample size	parameters	X_1	X_2	X_3	X_4
$\alpha = 0.3$	20	a	1.0972	1.1539	1.7810	1.2568
		α	0.8086	0.0677	0.2086	0.6535
	50	a	1.1256	1.2700	1.4396	1.0303
		α	0.8216	0.7157	0.6865	0.6168
	150	a	1.2496	1.0897	1.6343	1.2559
		α	0.3325	0.7673	0.0678	0.3562
threshold value	sample size	parameters	X_1	X_2	X_3	X_4
$\alpha = 0.4$	20	a	1.3016	1.7495	1.8991	1.6267
		α	0.6318	0.0528	0.5657	0.3907
	50	a	1.7449	1.4367	1.7119	1.2760
		α	0.9446	0.6051	0.7316	0.7825
	150	a	1.0152	1.1013	1.6643	1.2833
		α	0.8496	0.2661	0.0118	0.3448
threshold value	sample size	parameters	X_1	X_2	X_3	X_4
$\alpha = 0.5$	20	a	2.7861	2.8795	2.7061	2.8833
		α	1.5097	1.9187	1.6206	1.9606
	50	a	2.5372	2.0449	2.3278	2.6362
		α	1.4528	1.2119	1.1769	1.1561
	150	a	2.6387	2.5853	2.4671	2.8264
		α	1.2168	1.2224	1.3591	1.2720

Table (2) Estimation of Fuzzy Regression Parameters Using LS Method when $\sigma^2 = 1$ with different thresholds and different sample sizes

threshold value	sample size	Parameters	X_1	X_2	X_3	X_4
$\alpha = 0.3$	20	a	1.4186	1.6986	1.1881	1.2116
		α	0.6585	0.5662	0.3047	0.6876
	50	a	1.6101	1.5452	1.9295	1.9292
		α	0.2069	0.8189	0.5128	0.3369
	150	a	1.3993	1.7202	1.5905	1.9849
		α	0.4365	0.7505	0.7525	0.9340

threshold value	sample size	parameters	X_1	X_2	X_3	X_4
$\alpha = 0.4$	20	a	1.3756	1.2352	1.0967	1.8255
		α	0.2759	0.5148	0.7038	0.0140
	50	a	1.8137	1.8892	1.3717	1.3405
		α	0.8952	0.4665	0.0547	0.0039
	150	a	1.8236	1.3702	1.3867	1.6055
		α	0.2967	0.0044	0.3495	0.8984
threshold value	sample size	parameters	X_1	X_2	X_3	X_4
$\alpha = 0.5$	20	a	2.9704	2.0397	2.8165	2.1777
		α	1.8126	1.6454	1.0212	1.9006
	50	a	2.1409	2.4837	2.1173	2.8713
		α	1.7175	1.4398	1.5755	1.8550
	150	a	2.1904	2.0782	2.7426	2.5266
		α	1.1362	1.0978	1.3272	1.5443

Table (1), and (2) show the parameters of the estimated fuzzy linear regression model, where the difference in the cut off limit of the belonging function, the sizes of the different variables using the fuzzy maximum likelihood method (MLE), the fuzzy least squares (LS) method, the fuzzy moments method (Moment) method, and the fuzzy Bayesian method. It can be noticed that the fluctuation of the parameters with increasing its value decreases with increasing variance, except in the case of $\alpha = 0.5$.

Table (3) shows the values of the mean squares of error criterion for the Fuzzy Regression model when the value of

$\sigma^2 = 0.1$ according to the sample sizes and the ellipsis limit of the affiliation function.

Table (4) shows the values of the mean squares of error criterion for the Fuzzy Regression model when the value of

Alpha	sample size	L S	M L E	M O M	bayesian	best method
0.3	20	0.5358	0.6991	0.9483	0.3302	Bayesian
	50	0.4537	0.6597	0.3192	0.1480	Bayesian
	150	0.4344	0.0435	0.2120	0.1456	MLE
0.4	20	0.8967	0.8477	0.8450	0.7821	Bayesian
	50	0.7478	0.8120	0.2767	0.5861	MOM
	150	0.2682	0.4446	0.1043	0.0170	Bayesian
0.5	20	0.8477	0.8450	0.7821	0.8967	MOM
	50	0.8120	0.2767	0.5861	0.7478	MLE
	150	0.4446	0.1043	0.0170	0.2682	MOM

$\sigma^2 = 0.5$according to the sample sizes and the ellipsis limit of the affiliation function.

Analysis of simulation results:

To clarify the picture of the tested results and analyze them to measure the width of the fuzzy regression based on the

Alpha	sample size	L S	M L E	M O M	bayesian	best method
0.3	20	0.5324	0.8204	0.6626	0.1865	Bayesian
	50	0.2638	0.2878	0.6560	0.6795	LS
	150	0.2145	0.9722	0.8101	0.3872	LS
0.4	20	0.7895	0.6688	0.8901	0.6142	Bayesian
	50	0.5384	0.0814	0.6038	0.5168	MLE
	150	0.4369	0.0156	0.5103	0.1891	MLE
0.5	20	0.7403	0.3312	0.9450	0.6395	MLE
	50	0.6133	0.2460	0.8216	0.3645	MLE
	150	0.1321	0.1565	0.7419	0.0810	Bayesian

mean square error test and the results were as takes after:

We can note that the finding of Table (3) shows that the best estimator, when the sample size n = 20 is the Bayesian estimator, and the cutoff parameter alpha is = 0.3, and level of fluctuation is$\sigma^2 = 0.1$. When the test estimator is expanded (sample size = 50), we notice that the best estimator is the Bayesian estimator, and when the sample size is expanded to 150, we notice that the (MLE) estimator is the best among the rest of the estimators, and the results also showed that there is no change in the (MSE) values. With the increase in the test scale, it is known as the MSE values decrease as the test scale expands. Estimator (MLE), when the sample size estimate is 20, the cutoff parameter alpha=0.4, and the level of variation $\sigma^2 = 0.1$. When the sample size measure is expanded to 50, we notice that the best estimator is (MLE), and by expanding the sample size measure to 150, the (MLE) estimator became the first among the estimators, and the results showed that there is no fluctuation in the (MSE) values with the increase within the sample size estimate. It was noted that the MSE values decrease as the sample size estimate expands, and it appears that the best estimator is the Bayesian estimator when Sample size estimate 20, the cutoff parameter alpha = 0.5, and the level of volatility.$\sigma^2 = 0.1$, When the sample size measure increases to 50, the Bayesian estimator is also the leader, and by expanding the test estimate to n = 150, the Bayesian estimator becomes the best between the two estimators. This also shows that there is no change in the MSE values with the increase within Test estimation, it is known also the MSE values decrease with increasing sample size, and from this we conclude that the best estimator when $\sigma^2 = 0.1$ The cutoff parameter alpha = 0.3 is the Bayesian estimator, and when alpha = 0.4, the MLE estimator is the most excellent. By expanding the cutoff constraint level to alpha = 0.5, the Bayesian estimator is again the most excellent.

We can note that the results of Table (4) shows that the Bayesian estimator is the best estimator when the sample size is 20, the cutoff parameter alpha = 0.3, and the level of variation $(\sigma^2 = 1)$. When the sample size estimate is expanded to 50, the estimator (LS) becomes at the forefront, and by expanding the sample size measure to 150, the estimator (LS) becomes the best among the rest of the estimators. The results also show that there is no discrepancy between the (MSE) values with the increase in the sample size measure. It became famous that The MSE values decrease as the sample size estimate expands, and when the sample size estimate is 20, the cutoff parameter alpha = 0.4, the volatility level $(\sigma^2 = 1)$. When the sample size estimate of 50 expanded, the estimator (MLE) is also the leader, and by increasing the sample size estimate of

150, the estimator (MLE) becomes the leader among the rest of the estimators. It appears that the best estimator is the estimator (MLE), as the sample size measure is 20 and the cutoff parameter alpha is = 0.5 and the volatility level $(\sigma^2 = 1)$. And when the sample size measure is expanded to 50, the MLE estimator is also the most distinguished, but when the sample size estimate is expanded to 150, the Bayesian estimator becomes the best among the estimators. The results showed that there is no change in the MSE values with the expansion of the test size. It was known that what follows further shows that there is no fluctuation in the values of (MSE) with an increase within the sample size scale. It is known that the values of (MSE) decrease with the expansion of the sample size estimate, and from this we conclude that the leading estimator when$(\sigma^2 = 1)$, the cutoff parameter alpha = 0.3 is the best estimator (LS) and when alpha = 0.4, the MLE estimator is the most excellent. By extending the cutoff restriction level to alpha = 0.5, the MLE estimator is in addition to the leading one. Based on the robust error squares for all cases. We note that the best estimator for evaluating fuzzy regression is the Bayesian estimator, followed by the moment estimator (MLE) and the very poorest estimator was the minute estimator (M) and (LS).

Conclusions:

The study showed some conclusions and were included as follows:

1. We observe an increase in variance with the fluctuation of parameters (rising and falling their values) and using the method of maximum possibility (MLE), the method of least squares (LS), the method of moments (Moment) and the Bayesian method, except in the case of $\alpha = 0.5$, the estimators reserve the range of values for the parameters.
2. Note that the values of (MSE) do not fluctuate in with increasing sample size.
3. We note that the Bayesian estimator is the best estimator for estimating the fuzzy regression model, followed by the second place (MLE) and the worst estimator was the moment estimator (MOM) and (LS).

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